Evaluating the Adequacy of the Deposit Insurance Fund: A Credit-Risk Modeling Approach

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Abstract

As part of an effort to measure risk effectively, the FDIC hired Oliver, Wyman & Company to develop a credit-risk model for the deposit insurance funds. I use the credit-risk model to estimate the FDIC's loss distribution; and I perform sensitivity analysis using different assumptions about the parameters of the model. The sensitivity analysis results in a range of possible credit ratings associated with the deposit insurance funds. Under one set of assumptions, the deposit insurance funds would not warrant a BBB rating, whereas under another set of assumptions the funds would warrant an A- rating. The model provides useful quantitative information on the risks to the deposit insurance funds. Given the sensitivity of the results to different assumptions, however, the model should be used with caution.

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Introduction

In recent years, an increasing number of financial institutions in the United States and abroad have been using credit-risk models to evaluate the risk of their loan portfolios.[1,2] In January 2001, the Basel Committee issued a consultative paper on a new capital accord that would allow qualifying banks to use internal credit-risk models to calculate regulatory capital.

The FDIC is looking to credit-risk models, similar to those used by large financial institutions, as a means of measuring risk to the deposit insurance funds. As part of this effort, Oliver, Wyman & Company (OWC) developed an application of credit-risk models that explicitly constructs the loss distribution for the FDIC. The FDIC can use the model developed by OWC to evaluate fund adequacy.[3]

Before fully incorporating any credit-risk model into its current risk management practice, the FDIC should perform a validation of the model. There are essentially three components of model validation: sensitivity analysis, backtesting, and stress testing. This article focuses on the first component—sensitivity analysis.[4]

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[1] Financial institutions also use internal risk-management models, also known as value-at-risk (VaR) models, to estimate the value at risk in their trading books. *See* Nuxoll (1999) for more detail.

[2] A survey conducted by the Bank for International Settlements (1999) addressed other applications for credit-risk models. The survey found that financial institutions were using credit-risk models to set concentration and exposure limits, set hold targets on syndicated loans, price loans on a risk basis, improve the risk/return profiles of the portfolio, evaluate the risk-adjusted performance of different business lines or managers, allocate economic capital, and set and value loan-loss reserves.

[3] The FDIC can also potentially use the CLD model developed by OWC to evaluate alternative risk-based deposit insurance pricing options. Since the model uses a bottom-up approach, it can be used to measure the contribution of an individual institution to the overall risk to the insurance funds, as discussed in Hanweck (2001) and Kuritzkes et al (2001).

[4] Backtesting entails comparing ex ante estimations with ex post experience. Stress testing involves analyzing the effects of alternative economic scenarios (represented by alternative sets of parameters) on the model output. In contrast to changing many parameters as in stress testing, sensitivity analysis focuses

Sensitivity analysis involves analyzing the effect of making different assumptions about model parameters on the output from the model.[5] The accuracy of the parameters as representations of the future, and the validity of the model assumptions, determine the overall reliability of a credit-risk model. Unfortunately, most financial institutions currently do not conduct sensitivity testing on the parameters or assumptions embedded in their credit-risk models. The few practitioners who have conducted sensitivity analysis observe that the measurement of credit risk in a portfolio typically depends more on the quality of the information used by the model than on the details of the modeling approach. In fact, Koyluoglu and Hickman (1998a, 1998b) and Gordy (2000) demonstrate that alternative credit-risk modeling approaches are essentially equivalent. However, the sensitivity analysis that has been conducted indicates that model outputs are sensitive to changes in model parameters, especially changes in probabilities of default (PDs), loss given default (LGD), and default correlations.[6] This article focuses on the sensitivity analysis of these three inputs.

The first section of the article describes credit-risk models and their application to risk evaluation. I compare how credit-risk models are used by financial institutions to how the FDIC can potentially use credit-risk models to evaluate risk to the deposit insurance funds. The next section describes in detail the derivation of the inputs to the model (exposure, probabilities of default, loss given default, and default correlation bucketing) and discusses results from a set of baseline simulations. The following three

on the effects of changing one parameter. *See* BIS (1999) for more information on the validation of credit-risk models.

[5] Although by definition parameters are fixed in a model, there is still some uncertainty associated with them. Sensitivity analysis investigates this parameter uncertainty.

[6] *See* BIS (1999).

sections discuss the results from the sensitivity analysis performed on three of the inputs: probabilities of default, loss given default, and default correlation bucketing. The final section provides concluding remarks.

The Credit-Risk Model

Credit-risk models were developed to measure risk in a portfolio of individual loans. Applying credit-risk models to evaluate the risk to the deposit insurance funds requires viewing the funds as a portfolio of risks. The components of the portfolio are not individual loans but exposures to individual insured institutions. The FDIC's exposure to individual banks can be aggregated to arrive at a cumulative loss distribution. Each institution has a small, but non-zero, chance of failing and thereby causing a possible loss to the deposit insurance funds. In general, there is a high probability of a small loss to the insurance fund. There is also a positive probability that the insurance funds will incur large losses either from the failure of a large bank or from the failure of a large number of banks.

Evaluating the risk in a portfolio of loans differs in significant ways from evaluating the risk in the deposit insurance funds. Although it seems reasonable to make the analogy between the risk associated with holding a portfolio of loans and the risk associated with insuring a portfolio of banks, clearly the default event is different. The default of a loan means an obligor is unable to make scheduled payments. Although defaults on individual loans usually contribute to the failure of a bank, typically banks fail because of a combination of a wave of individual loan defaults and poor policies, procedures, and management. Another distinction between the default on a loan and the failure of a bank is that the failure of a bank is a regulatory event: only the regulatory authority can close a bank. Despite these differences, the credit-risk model can be useful as a way to explicitly model potential losses and quantify risk to the deposit insurance funds.

There are two types of credit-risk models: default and mark to market. The default models focus on two outcomes—default or no default. The mark-to-market approach models the migration from one credit rating to another. The default model is the most common approach used to analyze the loan portfolio of a bank and is the type of model used in this analysis.

The primary output of a credit-risk model is a distribution of losses, or a cumulative loss distribution (CLD). From the CLD, one can calculate the expected loss and the unexpected loss. The expected loss, which is equivalent to the mean of the CLD, is the amount of loss one would expect to experience in a portfolio over the chosen time horizon. The unexpected loss, or the deviation from the expected loss, measures the amount of risk in the portfolio. One measure of risk is the volatility of the potential loss around expected loss, or the standard deviation of the CLD.[7]

The FDIC can look at expected loss generated by a credit-risk model as a measure of the amount of reserves needed to cover these losses over the coming year.[8] Financial institutions use credit-risk models to estimate the economic capital needed to support their credit-risk exposures. The role of loss reserving is to cover expected credit losses.[9]

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[7] To be consistent with the terminology used by Oliver, Wyman & Company, I call the standard deviation of losses the unexpected loss.

[8] The FDIC currently uses an actuarial method to set its loss reserves.

[9] Generally Accepted Accounting Principles (GAAP) require reserving for probable and estimable losses. As discussed in Jones and Mingo (1998), the role of reserving policies is to cover expected losses. In the context of this article, expected losses are the product of the probability of incurring a loss multiplied by the estimated loss and are thus both probable and estimable.

The role of economic capital is to cover unexpected losses. The FDIC can also use a credit-risk model to evaluate the adequacy of the deposit insurance funds to cover unexpected losses—analogous to financial institutions setting the appropriate level of economic capital.

Observed distributions of credit losses on loan portfolios are not normally distributed (see Figure 1).[10] The observed distributions are typically skewed toward large losses: for a given mean and standard deviation, the probability of incurring large losses is greater than it would be if the distribution were normal. Similarly, the FDIC faces a skewed distribution of losses: in any given period, there is a high probability of incurring small losses from the failure of a number of small banks but a small probability of incurring large losses from the failure of a large bank and/or the failure of a large number of banks.[11] Since the distribution is skewed, precise estimation of the high quantiles in the distribution is important. The size of the estimation error in this region of the distribution can potentially be large and have a large influence on the shape of the distribution, and thus the measures of risk.

Financial institutions typically collapse the estimated CLD into easy to understand measures. Similarly, this paper collapses the estimated CLD into a simple measure—for each CLD that results from a simulation, the reserve ratio that is required to earn a particular credit rating is presented.

The reserve ratio is the ratio of the size of the fund to insured deposits. Under current law, the FDIC is required to maintain a target level of funds relative to the

[10] *See* Jones and Mingo (1999, 1998).

[11] *See* Kurtizkes et al (2001) for a visual representation of the loss distribution for the FDIC from 1934-2000.

amount of insured deposits in the industry. The target level, or designated reserve ratio (DRR), is constant and set at 1.25. If the insurance funds are above the 1.25 DRR, the FDIC is prohibited from charging insurance premiums to institutions that are well capitalized and well managed.[12] The DRR explicitly links the level of the insurance funds to the amount of exposure, measured by total insured deposits.

A credit rating can be mapped into an analogous solvency standard. Many financial institutions choose a solvency standard that is consistent with their desired credit rating.[13] For example, if a financial institution is willing to accept a minimum of a 99.97 percent probability that losses will exceed the capital level, or the equivalent of a AA rated corporate bond, it can calculate the amount of capital it needs to achieve that solvency standard. Similarly, the FDIC can use the cumulative loss distribution from a credit-risk model to determine what reserve ratio is required to reach a chosen solvency standard. For example, the FDIC may be willing to accept a minimum of 99.97 percent chance that the fund will not incur losses larger than the fund balance, again which is equivalent to a AA credit rating.[14] For the simulation results presented in this paper, we

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[12] In Section 7(b) of the FDI Act, the FDIC is prohibited from charging assessments in excess of the amount needed to maintain the reserve ratio at the DRR unless an insured depository institution exhibits "financial, operational, or compliance weaknesses ranging from moderately severe to unsatisfactory, or is not well capitalized."

[13] For more detail, see Jones and Mingo (1999, 1998).

[14] Although a credit rating is a useful summary measure, there is a difference between the credit rating for a corporate bond and a credit rating for the deposit insurance fund. Credit ratings for corporate bonds reflect the risk that a bond will default. However, the FDIC would never default even if the deposit insurance funds became insolvent: the FDIC honors all deposit claims and has the full-faith-and-credit backing of the federal government. For this reason, some may argue that the potential insolvency of the deposit insurance funds is irrelevant. However, funds that are borrowed from the Treasury to cover any insolvency must eventually be repaid. In addition, according to the Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA), the deposit insurance funds must be recapitalized through assessments on insured institutions.

used the mapping between bond ratings and default probabilities from the Oliver, Wyman & Company methodology. (See Table 1.)

To evaluate the adequacy of the deposit insurance funds, I focus on the credit rating that the December 31, 2001, fund balances earn. Since the FDIC does not have a desired credit rating in mind, I report the reserve ratio that would be required to earn an A, A-, BBB+, or BBB credit rating.

For all simulations, I investigate fund adequacy for the Bank Insurance Fund (BIF) and for a hypothetical merged fund that includes institutions insured by the BIF and the Savings Association Insurance Fund (SAIF). Currently the BIF and SAIF are two separate insurance funds, and the FDIC calculates and implements separate deposit insurance assessments for each. However, since the FDIC has long held that the two funds should be merged, I demonstrate the effect of a merger on fund adequacy.

In a default model, the expected dollar losses (EL) are the sum over the portfolio of the individual exposures (EXP_i) times the estimated probability of default (PD_i) times the expected loss given default (LGD_i).[15]

$$EL = \sum_{i=1}^{n} EXP_i \times PD_i \times LGD_i$$

Estimating unexpected losses for the portfolio involves two steps. First, calculate a measure of the unexpected losses for an individual asset in the portfolio (UL_i). One measure of risk is the standard deviation of losses, which I call unexpected losses.[16]

[15] This description of the CLD model is intentionally brief. For more detailed discussion see Jorion (2001), Ong (1999) and Crouhy et al (2001).

[16] This calculation assumes exposure (EXP_i) is not stochastic.

$$UL_i = EXP_i\sqrt{PD_i \times \sigma^2_{LGD_i} + LGD_i^2 \times PD_i(1 - PD_i)}$$

Second, aggregate the volatility of the individual assets into a measure of volatility for the portfolio, taking into account the correlation of default between assets ρ_{ij}, and take the square root.

$$UL = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}\rho_{ij} UL_i UL_j}$$

This simple structure makes it clear that the estimates of all of the parameters PD_i, EXP_i, LGD_i, and ρ_{ij} play an important role when expected and unexpected losses for the portfolio are estimated. The quality of these estimates can have a material effect on the accuracy of portfolio credit models.

As in the basic framework above, the expected loss for each institution is the product of the probability of default (PD_i), the exposure (EXP_i), and the loss given default (LGD_i). One of the crucial decisions when a credit-risk model is being constructed is the time horizon. Financial institutions commonly use a one-year planning horizon, since this is the period over which they can take actions that will mitigate the risk. The analysis in this paper also employs a one-year time horizon.[17] Hence, expected losses measure the anticipated average annual loss.

The total expected loss for the deposit insurance fund is the sum of expected losses for each individual institution insured by the fund. Unexpected loss is the anticipated volatility of loss defined as one standard deviation of loss. The CLD model uses Monte Carlo simulation techniques to generate an empirical distribution of the cumulative loss distribution for the FDIC.[18]

[17] BIS (1999) discusses the time horizon typically chosen by financial institutions. Banks typically do not test their credit models for sensitivity to the chosen time horizon as discussed in Jones and Mingo (1999, 1998).

[18] Appendix A describes the CLD model and the simulation methodology in more detail.

The inputs to the CLD model are the three elements described above (probability of default [PD_i], exposure [EXP_i], loss given default [LGD_i]) and a correlation matrix consisting of the elements $\rho_{ij.}$ To simplify the estimation of the correlation matrix, the model requires that institutions be grouped into buckets. The analysis below presents simulations the resulted from changing each of these elements and examines the results.

Baseline Simulations

In the sensitivity analysis, I hold a few elements constant across all simulations. All PDs are for a one-year horizon, and LGD is assumed to be a random variable. Although the CLD model allows for a two-state simulation, I use only the one-state version of the model for all simulations.[19] I assume there are five factors, an assumption implying that the model estimates 25 separate correlation coefficients (ρ_{ij}). I ran all simulations for 50,000 iterations.

<u>Exposure</u>

In the baseline simulations, exposure for each institution is defined as the total assets of the institution reported on the December 31, 2001, Call Report.[20] One can argue that the FDIC's exposure is significantly less that the total assets of an institution. Some have argued that the FDIC's exposure is limited to the amount of insured deposits. However, using the amount of insured deposits presents data problems. First, the amount of insured deposits reported on the Call Report is an estimate. Second, the measures of

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[19] The CLD model allows for simulations using either one or two states. A two-state model allows for the definitions of different parameters for a good state and a bad state. The two-state model allows the user to set the percentage of states that are good versus bad.

[20] The data used in the analysis are from the Call Report and were retrieved in July 2002. Therefore, they reflect any revisions made between December 2001 and July 2002.

loss given default (discussed below) are available only in terms of total assets. Insured deposits are not measured at the time of closure for all institutions that fail, but only for institutions that are resolved in such a way that the FDIC is required to determine which deposits are insured.[21] Defining exposure as total assets does not distort the results of the model since loss given default is measured in terms of losses on total assets.[22]

When I evaluate the BIF separately from the SAIF, the exposure of individual institutions must take into account that some institutions hold both BIF- and SAIF-insured deposits. In all the simulations for the BIF, I allocate exposure (total assets) to the appropriate insurance fund on the basis of the BIF- and SAIF-insured deposit levels in the institution. If, for example, an institution that has the BIF as its primary insurer acquires a SAIF-insured institution, the acquirer must separately report the acquired SAIF-insured deposits for insurance assessment purposes (along with its own BIF-insured deposits). All acquired deposits are known as Oakar deposits, named after the sponsor of the legislation allowing these types of acquisitions.[23] Under my asset allocation method, if an institution has 25 percent of its domestic deposits as SAIF insured and 75 percent as BIF insured, then 25 percent of its exposure is allocated to the SAIF and 75 percent to the BIF. This is consistent with the approach that the FDIC uses to allocate to the BIF and SAIF the resolution costs that are associated with failed banks.

[21] The FDIC estimates insured deposits before the time of failure but does not make a final insurance determination unless such a determination is required for completing the resolution of the failed bank.

[22] The total loss figures measure the loss to the deposit insurance funds and take into account the extent to which losses are smaller because the FDIC shares losses with uninsured domestic depositors.

[23] See the Federal Deposit Insurance Act (12 U.S.C. 1815 Section 5(d)(3)).

Probabilities of Default

The probabilities of default used in the baseline simulations are derived from a mix of market information and historical experience. When available, the probabilities of default are translated from the credit rating on long-term debt. If credit rating information was not available, an unconditional measure of the probability of default was used.

I used bond ratings for December 2001 from Standard and Poor's (S&P).[24] I translated the bond ratings to probabilities of default using the mapping provided to the FDIC by OWC.[25] Although the number of institutions (249) that had market information may seem small, the market information represents approximately one-half of the total for all BIF- and SAIF-insured institutions in terms of total assets, total deposits, and approximately one-third of insured deposits. (See Table 2.)

For the institutions that did not have credit ratings available, I calculated PDs using the number of failures from 1934 to 2001 as reported in the FDIC's 2001 Annual Report. There were 8,115 BIF and 1,265 SAIF institutions that were assigned the historical average of 24 basis points in the baseline simulation.

Loss Given Default

When the credit-risk model framework is used to evaluate deposit insurance fund adequacy, loss given default is the loss incurred when an institution fails. As mentioned above, total assets are the equivalent of "exposure" for all of the simulations. Therefore,

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[24] To match the S&P ratings to individual institutions, I used a mapping between ticker symbols and certificate numbers developed by Gary Seale, FDIC, Division of Insurance and Research. I would like to thank him for providing me with the mapping.

[25] See Appendix B for a discussion of the mapping provided by OWC.

loss given default is expressed as the loss on assets (total losses as a percentage of total assets). As also mentioned above, loss given default is a random variable in the CLD model. Since the model assumes that loss given default is random, the mean and standard deviation of loss given default are inputs into the CLD model.[26]

For the baseline simulation, I constructed the mean and standard deviation of loss given default from a 15-year history of FDIC losses, which is available from the FDIC's *Failed Bank Cost Analysis*. I split failures into five size groups and calculated the mean and standard deviation of the loss rates on assets.[27] (See column 2 of Table 3.) In the simulations, each institution was assigned a mean and standard deviation of loss rates on the basis of the size of the institution.[28]

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[26] The model assumes LGD follows a log-normal distribution. Under this assumption, the mean and standard deviation are sufficient statistics to describe the distribution of LGD. Haluk Unal and Dilip Madan from the University of Maryland have done some interesting research exploring the statistical distribution of losses to the FDIC. This research is unpublished as of the date of this paper.

[27] Note that the number of observations in each cell will not match other publicly available data on the number of failed banks. To be consistent with calculations performed by the Division of Finance at the FDIC, I consolidated 202 of the receiverships into the following 13 groups:

1. BankTexas, Inc (11 institutions, failed 1987)
2. First City (59 institutions, failed 1988)
3. First Republic (41 institutions, failed 1988)
4. Alliance (2 institutions, failed 1988)
5. Texas Bank North (2 institutions, failed 1988)
6. Mcorp (20 institutions, failed 1989)
7. Texas American Bancshares (24 institutions, failed 1989)
8. National Bancshares (9 institutions, failed 1990)
9. Bank of New England (3 institutions, failed 1991)
10. Southeast Bank (2 institutions, failed 1991)
11. New Hampshire Banks (7 institutions, failed 1991)
12. First City (20 institutions, failed 1992)
13. Merchants Bank (2 institutions, failed 1992)

[28] Accordingly, the 4,535 BIF-insured institutions in the sample with assets less than $100 million as of December 31, 2001, would be assigned a loss given default mean of 24.06 percent and a loss given default standard deviation of 13.87 percent.

Bucketing

As mentioned above, another input into the CLD is the bucketing of institutions to facilitate the estimation of the correlation matrix. The model treats the stochastic properties of the defaults of institutions within each bucket the same. Therefore, it is important to put institutions that are expected to have similar default characteristics in the same bucket. I group borrowers into 25 discrete buckets on the basis of observable characteristics.

For the baseline simulations, institutions were sorted by size, and each of the 20 largest institutions was placed in its own bucket. The remaining institutions were placed in five buckets on the basis of size. These five buckets correspond to the five size categories used for calculating loss given default.

Simulation Results

Using the baseline assumptions would give the BIF a credit rating worse than BBB. (See Figure 2.) The bars in Figure 2, and subsequent figures, indicate the reserve ratio for the fund to earn the corresponding credit rating. The horizontal line indicates the reserve ratio as of December 31, 2001.

In the baseline simulations the expected loss to the BIF is approximately $1.17 billion and the unexpected loss is $4.02 billion. (See Table 4.) To obtain an A rating for the BIF, the reserve ratio would have to be 2.84 percent. The reserve ratio of 1.26 for the BIF as of December 31, 2001 does not earn a BBB rating. The baseline simulation indicates that the BIF and SAIF merged fund has an EL of $1.64 billion and a UL of $5.23 billion. The reserve ratio for a merged BIF and SAIF fund would have to be 2.54

percent for the fund to earn an A credit rating. The reserve ratio of 1.29 as of December 31, 2001, does not earn the merged fund a BBB rating. (See Figure 3.) It should be noted that the reserve ratio required for an A rating is lower for the BIF than for the BIF and SAIF merged, as would be expected from the effects of diversification.

Sensitivity Analysis: Probabilities of Default

The specification of the PDs is important in the simulations, as is evident in the equations for EL and UL.[29] I perform sensitivity analysis on the choice of PDs, using three alternative sources of PDs. First, I replace the market information used in the baseline simulation with solely the historical PDs. Second, I use an econometric model to generate PDs. Third, I investigate three different sources of market information other than the long-term debt ratings from S&P.

<u>Historical Probabilities of Default</u>

In the first attempt to measure sensitivity of the model to changes in the PD, I simply assign the historical PD of 24 basis points to all of the institutions. As a comparison of the first and second columns of Table 5 shows, using only the historical PDs increases both the EL and the UL of the distribution of losses. This simulation indicates that the reserve ratio for the BIF would have to be 3.76 percent to receive an A rating, and 2.69 to earn even a BBB rating. (See Figure 4.) The reserve ratio for a BIF and SAIF merged fund would have to be 3.37 percent to earn an A rating and 2.36 percent to earn a BBB rating. (See Figure 5.) By performing a rather simple experiment

[29] Carey and Hrycay (2001) also emphasize the importance of estimating the default probabilities accurately for use in credit-risk models.

(replacing the market-derived PDs with the historical PDs), I show that the amount of risk to the insurance fund, as measured by the CLD model, has increased dramatically.

Probabilities of Default from a Logit Model

A more sophisticated experiment involves generating probabilities of default from an econometric model. The econometric model I use is a logit model that uses financial ratios to predict the PD.[30] The model assumes that the probability of failure over a 12-month period is determined by the institution's financial condition as of the start of the period. Table 6 shows the estimated relationships. This model is then used to predict PDs on the basis of the December 2001 Call Report and examination data.

The first experiment replaces the PDs in the baseline simulation with the PDs generated by the logit model. (See Table 5.) The average PD produced by the logit model is much lower than the average PD used in the baseline, but the standard deviation is much higher. The EL for the BIF is much lower than the baseline—$376 million compared with $1.17 billion. Similarly, the UL is much lower—$2.7 billion compared with $4.0 billion. In fact, when the PDs generated by the logit model are used, the BIF would earn a rating of BBB. Similarly, the EL and UL for the BIF and SAIF merged fund decrease, and the merged BIF and SAIF would earn a rating of BBB+. (See Figures 4 and 5.)

[30] The logit model assumes that the probability of bank failure takes a logistic functional form and is, by definition, constrained to fall between 0 and 1. The dependent variable, the log of the odds-ratio, is assumed to be related linearly to the explanatory variables (the financial ratios). The model states that the likelihood of failure over a 12-month period is determined by the institution's financial condition as of the start of the period. Financial condition is measured by capital adequacy, asset quality, earnings, and safety-and-soundness examination ratings. The data used to estimate the model were year-end condition data and subsequent failures between 1984 and 2000 for commercial and savings banks and thrifts. (Thrift data were available only between 1991 and 2000.)

Now, instead of replacing all the baseline PDs with the PDs generated by the logit model, I replace only the historical PDs. The institutions with market information have the same PDs as in the baseline simulation. Again, the average PD is much lower than the average PD in the baseline simulation. (See Table 5.) The mix of market information and PDs from the logit model shows that the BIF would earn a BBB+ rating, and the BIF and SAIF merged fund would earn an A- rating. (See Figures 4 and 5.)

Overall, using the PDs generated by a logit model implies that risk to the insurance fund (as measured by the CLD model) is lower than in the baseline simulation. The PDs generated by the logit model are dependent on the financial condition of the insured institution at year-end 2001. Since most insured institutions were in good financial condition relative to historical periods, it is not surprising that using this model yields lower measures of risk.

Probabilities of Default from Market Information

In the baseline simulation, I mapped S&P ratings of long-term debt to PDs. I now perform a sensitivity analysis that looks at two other sources of market information. First, I replace the ratings on long-term debt with ratings on long-term deposits. Second, I use probabilities of default published by KMV in conjunction with historical PDs.

Long-Term Deposit Ratings

In these simulations, I replace the long-term bond ratings, provided by S&P and translated into PDs, with long-term deposit ratings translated into PDs.[31] I collected

[31] Long-term deposits are deposits that have a maturity of over one year.

credit ratings on long-term deposits from Bloomberg.[32] The sample contained 98 BIF and 105 BIF and SAIF institutions with long-term deposit ratings. Although the number of institutions with long-term deposit ratings is smaller than the number of institutions with ratings in the baseline, institutions in the former group still represent approximately one-half of the total for all BIF- and SAIF-insured institutions in terms of total assets, total deposits, and over one-third of insured deposits. (See Table 2.)

The simulation, which uses a combination of the PDs from the long-term deposit ratings and the historical PDs, results in approximately the same measured risk. The EL and UL both decrease slightly. (See Table 8.) The BIF would not earn a BBB rating; nor would the merged fund. (See Figures 6 and 7.) Replacing long-term bond ratings with long-term deposit ratings did not markedly affect the measure of risk.

Probabilities of Default from KMV

KMV developed a model of default probability, Credit Monitor, that uses equity prices and financial statements. The model relates the market value of a firm's assets (which is the sum of the market value of equity plus the market value of debts) to the probability of default.[33]

Using a mapping between ticker symbols and bank certificate numbers, I assigned KMV PDs to 887 BIF and SAIF institutions. These institutions account for approximately one-half of the total assets, total deposits, and total insured deposits in the BIF and in the BIF and SAIF merged. (See Table 2.) When the KMV PDs are used in

[32] The long-term deposit ratings were collected on July 16, 2002 and July 20, 2002. I match the long-term deposit rating using the same mapping from ticker symbol to certificate number that I used for the bond ratings.

[33] See Appendix C for a discussion of the KMV model.

combination with the historical average PD of 24 basis points, the average PD is higher than the baseline and the standard deviation of the PD is much higher--approximately five times higher. (See Table 7.)

The risk to the insurance funds, as measured by the CLD increases dramatically when the PDs from KMV are used. The EL for the BIF increases from the baseline of $1.17 billion to $2.50 billion, and the UL increases from the baseline of $4.02 billion to $7.70 billion. The EL for the BIF and SAIF merged increases from a baseline of $1.64 billion to $3.17 billion; similarly the UL increases from the baseline of $5.30 billion to $8.98 billion. The reserve ratios for the BIF and in the BIF and SAIF merged fund are well below the reserve ratios required for a BBB credit rating. (See Figures 6 and 7.) The PDs from KMV are based on equity prices, which tend to be volatile. The higher standard deviation of the PDs had a large influence on the amount of risk measured by the model.

Sensitivity Analysis: Loss Given Default

In the baseline simulation I defined loss given default as an average loss rate calculated from 1986–2001 using the FDIC's *Failed Bank Cost Analysis*. However, losses incurred by the FDIC varied over time during that 15-year period. I performed sensitivity analysis using loss given default calculated over different time periods. The first simulation in the loss given default sensitivity analysis replaces the 15-year average with the more recent loss experience from 1990–2001. The remaining simulations for the sensitivity analysis on loss given default involve averages over relatively low loss rate periods and relatively high loss rate periods. I chose the relatively high loss period, 1986–1989, and the relatively low loss period, 1990–1993, by examining the loss data and grouping the years accordingly. Table 3 shows the mean and standard deviation of loss rates for the different periods.

The first simulation run for loss given default sensitivity analysis replaces the 15-year average with a more recent loss experience: an average over 1990–2001. The mean and standard deviation of loss given default is lower in this scenario. (See Table 8.) Using the more recent loss given default figures results in a lower EL and UL. The credit rating for the BIF improves from below a BBB rating to a BBB+ rating. (See Figure 8.) Similarly, the credit rating for the BIF and SAIF merged fund improves from below BBB for the baseline simulation to BBB+ when the 1990–2001 loss given default figures are used. (See Figure 9.)

When the 15-year averages are replaced by the average loss given default in the relatively high-loss period, both the mean and the standard deviation of loss given default increase. (See Table 8.) The EL and the UL both increase when the 1986–1989 loss rates are used. In this high-loss-rate scenario, the BIF reserve ratio would have to be 2.74 percent to earn a BBB credit rating. The reserve ratio for the BIF and SAIF merged would have to be 2.45, well above the current reserve ratio. (See Figures 8 and 9.)

The simulation using the relatively low loss rates from 1990–1993 results in a lower EL and UL. (See Table 8.) In this scenario, the mean and standard deviation of loss given default are both lower than the baseline. The BIF would earn a BBB+ credit rating under the low loss-given-default scenario; the BIF and SAIF merged would also earn a BBB+ credit rating. (See Figures 8 and 9.)

When the low-loss-rate period (1990–1993) is combined with the high-loss-rate period (1986–1989) the results are similar to the baseline. The EL and UL are slightly lower than the baseline. As in the baseline, the credit rating for the BIF would be below a

BBB; the credit rating for the BIF and SAIF merged would be below BBB. (See Figure 8 and 9.)

As one would expect, when an average loss given default that is calculated from relatively high-loss-rate-periods is used, the adequacy of the insurance funds drops. Conversely, when an average loss given default is calculated from a relatively low-loss-rate period, the adequacy of the insurance funds increases.

Sensitivity Analysis: Bucketing

As mentioned above, bucketing, or grouping institutions into separate buckets, simplifies the estimation of the relationship between defaults of different institutions. This method assumes that institutions within the buckets have the same default correlations with institutions outside the buckets. Therefore, when one constructs buckets, it is best to group institutions that have similar default characteristics. I conduct sensitivity analysis by grouping institutions, first using a simple grouping scheme and then using common characteristics that might cause them to weaken and fail together.

Equal Number of Institutions in Each Bucket, by Size

The first simulation takes a simple approach and separates the institutions in the sample into 25 buckets, with an equal number of institutions in each bucket. The institutions are first sorted by size; so, for example, the 334 largest BIF institutions are in the first bucket, the next 334 largest BIF institutions are in the next bucket, and so on. This simple bucketing approach causes EL to increase slightly and the UL to decrease for the BIF, and both the EL and UL to fall slightly for the BIF and SAIF merged. (See Table 9.) The measures of fund adequacy remain approximately the same—the BIF would not earn a BBB rating for the BIF, and the BIF and SAIF merged balance would not earn BBB rating. (See Figures 10 and 11.)

Size and Region

During the banking crisis of the 1980s and early 1990s, bank failures tended to be concentrated by region.[34] I separate institutions into buckets according to the five size categories used for the loss-given-default calculations and according to location in five regions of the United States: Northeast, Southeast, Central and Midwest, Southwest and West. (See Table 10.) The EL and UL are smaller than in the baseline simulation. (See Table 9.) Under this scenario, neither the BIF nor the BIF and SAIF merged would earn even a BBB rating.

CAMELS Ratings and Region

Institutions with similar supervisory ratings have similar default characteristics. In this simulation, I group banks by supervisory rating and by region.[35] As of December 2001, most institutions had a composite CAMELS rating of 1 or 2. (See Table 11.) Combining the five CAMELS ratings with the five regions results in 25 buckets.

Including CAMELS groups instead of size buckets leads to slightly higher measures of risk. (See Table 9.) The BIF would not earn a BBB rating, and the merged BIF and SAIF would not earn a BBB rating. (See Figures 10 and 11.)

[34] Regional concentration may not be the case in the future, since the law now permits interstate banking. Thus, institutions may now diversify risk across regions.

[35] Supervisory, or CAMELS, ratings range from 1 to 5 (1 being the best). Regulatory agencies consider institutions with composite ratings of 4 or 5 to be problem institutions.

CAMELS Ratings and Size

If I combine the CAMELS rating and size buckets, I am only able to populate all 25 buckets required by the CLD model for the BIF and SAIF merged fund. For the BIF and SAIF merged fund, combining the CAMELS ratings with size rather than region results in slightly higher EL and a slightly lower UL. (See Table 9.) Again the BIF and SAIF merged fund would not earn a BBB rating. (See Figures 11.)

Specialized Lender and Region

Banks with exposures to similar types of lending or banks with similar business lines are likely to experience difficulties at the same time. For example, if a drought occurs, one would expect agricultural banks to begin having difficulties. Accordingly, I group banks into specialized lending groups.[36]

When I combine five of the specialized lenders (agricultural, consumer, commercial, mortgage, and multinational) with the regions, four buckets do not have any institutions in them. (See Table 12.) The remaining institutions are put into the four remaining groups by type: other large, other large specialized, other small specialized and other small institutions. The measures of risk (EL and UL) are slightly higher than in the baseline simulations. (See Table 10.) At the December 31, 2001 reserve ratios, neither the BIF nor the BIF and SAIF merged would earn a BBB rating. Overall, the results from the CLD model are more robust to changes in bucketing than to changes in the other inputs.

[36] Appendix D presents the details of the derivation of the specialized lending groups.

Conclusions

As measured by the CLD model developed by Oliver, Wyman and Company for the FDIC, the credit rating of the deposit insurance funds is sensitive to different assumptions about the probabilities of default and the loss given default. Under one set of assumptions the deposit insurance funds as of December 31, 2001 would not warrant a BBB rating, whereas under another set the deposit insurance funds would warrant an A- rating.

The results from the CLD model were sensitive to changes in the PDs. When six different sets of PDs were used, the credit rating as of December 31, 2001 for both the BIF and the BIF and SAIF ranged from below BBB to A-. Under different assumptions for the PD, the reserve ratio required to earn a BBB rating ranged from 0.92 to 2.69 earn a BBB rating and to earn an A rating ranged from 1.75 to 3.76.

The model was most sensitive to changes in loss given default. When average loss given default from recent periods and periods of low loss rates was used, the BIF and the BIF and SAIF merged funds were both rated BBB+. When average loss given default from high-loss-rate periods was used both the BIF and the BIF and SAIF merged funds would not be investment grade. Under different assumptions for the LGD, the reserve ratio required to earn a BBB rating ranged from 0.89 to 2.74 and to earn an A rating ranged from 1.64 to 4.08.

The CLD model was less sensitive to changes in alternative bucketing techniques. Fund adequacy measures for the BIF and the BIF and SAIF merged did not change much: they were rated below BBB in all scenarios.

Certainly I have not exhausted the possibilities for sensitivity analysis. I could use more information, such as financial ratios, to form buckets. And, I have conducted sensitivity analysis of the CLD model only under the following conditions: random loss-given default, one state, with five factors. Any of these assumptions can be changed for a more thorough investigation of the model's sensitivity to the inputs.

There are other areas in which the model can be extended that may prove useful to the FDIC for risk assessment. As it currently stands, the CLD model is a static model evaluating fund adequacy for only one period. However, there are dynamic implications to fund adequacy (see Sheehan [1998] and Oshinsky [1999]). The model's response to multiyear simulations over the cycle and to stress testing also provides interesting research possibilities.

The model developed by OWC for the FDIC provides useful quantitative information about the risks faced by the deposit insurance funds and the adequacy of the funds. As part of the deposit insurance reform debate, there have been recommendations to eliminate the 1.25 designated reserve ratio and replace it with a wider band of accepted level of capitalization in the deposit insurance funds. Results from the model may be useful information to incorporate into a determination of acceptable levels of capitalization. However, this information must be used with caution because, as I have demonstrated with the sensitivity analysis, the model results can fluctuate under different reasonable assumptions.

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Appendix A
CLD Model Details

The CLD model developed by Oliver, Wyman & Company (OWC) for the FDIC evaluates the risks to the deposit insurance funds.[37] There are three basic types of models that can be used to evaluate either default or mark-to-market credit risks: actuarial, Merton based, and econometric. For example, CreditRisk+ is an actuarial model, CreditMetrics and Portfolio Manager are Merton-based models, and Credit PortfolioView is an econometric model. Koyluoglu and Hickman (1998a, 1998b) show that in theory the three types of credit-risk models are not very different. The results from the different models, provided the input parameters are equivalent, are virtually the same. The model developed by OWC for the FDIC is a combination of the actuarial and Merton approaches.[38]

Rather than estimate a correlation coefficient for each combination of individual institutions, the model estimates the correlation coefficients between the buckets of institutions. The model assumes that the defaults of institutions within a particular bucket move together.

More specifically, the model uses the method described here to generate the empirical distribution of cumulative losses to the FDIC. The model computes the average default correlation within the buckets and for the entire portfolio. Given these average default correlations, the model generates asset correlations between any two

[37] All discussion of the CLD model is based on OWC (2000a, 2000b, 2000c, 2000d) and meetings with OWC held at the FDIC in July through September of 2000. Also see Kurtizkes et al (2001).

[38] The discussion of the algorithm used in generating the model is based on the limited information that OWC provided to the FDIC. OWC provided a computer model to the FDIC but did not provide a description of all of the assumptions embedded in the model, nor did OWC provide the uncompiled source code used to generate the model.

buckets and uses this correlation matrix to drive a multivariate normal distribution. As in the Merton-based model, the CLD model assumes that asset values follow the multivariate normal distribution and that an individual institution defaults when the asset value falls below a critical point. The CLD model draws from a multivariate normal distribution with the implied asset correlation matrix and determines whether an individual institution defaults or not.[39] For the banks that fail in the simulation, the model calculates the expected loss (EL_i) as the product of exposure (EXP_i) and loss given default (LGD_i).[40] Then the model sums these individual expected losses to arrive at the expected loss for a simulation. Using Monte Carlo simulation techniques, the model repeats the simulation 50,000 times and generates an empirical distribution. The model then analyzes the sample set of 50,000 cumulative losses to calculate expected and unexpected losses and to evaluate fund adequacy.

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[39] The CLD model uses principal component analysis to drive the simulation of the normal variates from the asset correlation matrix. Principal component analysis helps to generate simulations when the correlation matrix is known.

[40] The CLD model allows the user to chose whether loss given default is constant or a random variable. When loss given default is a random variable, the model assumes that it follows a log-normal distribution. Under this assumption, for each bank that fails the model draws loss given default from a log-normal distribution with a given mean and standard deviation and uses it to calculate expected losses. In unpublished research, Haluk Unal and Dilip Madan from the University of Maryland investigate the distribution of losses to the FDIC.

Appendix B
Mapping between Credit Ratings and Probabilities of Default

OWC developed a methodology to map S&P credit ratings to probabilities of default. (See Table B.1).[41] This methodology used information from all industries, not just the financial industry.

Since the PD is an important input into the credit-risk model, it is essential to investigate the relationship between credit ratings and PDs. Additional information about this relationship is available from Standard and Poor's and Moody's. Both credit-ratings agencies conduct ongoing research into the default experiences of their rated issuers.[42]

Brand and Bahar (2000) calculated the historical one-year PD of corporations by Standard and Poor's credit ratings. Their study uses data from 1981 to 1999 for all U.S. and non-U.S. industrials, utilities, insurance companies, banks, other financial institutions, and real-estate companies. There are some differences between this study and the mapping generated by OWC. First, as shown on Table B.1, the historical one-year PDs are zero for corporations that have AAA, AA+, or AA ratings. In contrast, methodology developed by OWC assigns to institutions with those credit ratings one-year PDs of 0.01, 0.02, and 0.03 percent, respectively.[43] The OWC methodology assigned significantly higher PDs for other credit ratings as well: the PD assigned to institutions rated A+ was more than double the historical PD, and the PD assigned to institutions

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[41] OWC did not provide the FDIC with details regarding the methodology it developed to map credit ratings into probabilities of default.

[42] The definition of default differs slightly across these two rating agencies. Standard and Poor's defines default as the failure to pay any financial obligation. Moody's definition includes not only these defaults, but also the renegotiation of a financial instrument.

[43] The credit-risk model constructed by OWC does not allow for an PD of zero.

rated A- was triple the historical PD. The PDs assigned by OWC were not consistently higher for all of the credit ratings, however. OWC assigned a PD of 4.46 percent for institutions rated B, compared with an 8.46 percent historical PD; and OWC assigned a PD of 7.52 percent for institutions rated B-, compared with a 10.19 percent historical PD.

Using a proprietary database of ratings and defaults, Moody's calculates historical default rates for industrial and transportation companies, utilities, financial institutions, and sovereigns that have issued long-term debt to the public, including non-U.S. issuers. At the start of 2000, industrial companies represented 39 percent of rated firms, non-bank financials constituted 17 percent of rated firms, and banking institutions were 14 percent.[44] Keenan et al. (2000) calculated the one-year PDs shown on Table 2 using 1983–1999 data. There were six categories that had zero PDs according to the historical data; OWC assigned positive PDs to these categories. As in Table B.1, the OWC methodology assigned to some of the credit-rating categories PDs that were significantly higher. The PD assigned by the OWC methodology is more than three times the historical PD for institutions with a Baa1 credit rating and more than two times for institutions with a Baa2 credit rating. Most of the remaining PDs assigned by the OWC methodology were similar to the historical one-year default rates.

The difference between the mapping methods, historical or OWC, may affect the risk measurement and evaluation of fund adequacy generated by the credit-risk model. Of the 249 BIF and SAIF institutions that have credit ratings, about 60 percent were rated A, A+, or A- as of December 2001. The highest concentration, about one-third of the 249 institutions, had A+ credit ratings, and the OWC methodology assigned a 0.05 percent

[44] Keenan et al. (2000), 8.

PD compared with the historical one-year PD of 0.02 percent. Similarly for other groups with high concentrations of institutions, the OWC methodology either assigned higher PDs or, for one group, the same PD. Using the higher PDs causes the estimate of the EL to be higher. (See the equation for EL above.) The effect of using the higher PDs on the UL is not clear, since it will also depend on the correlations between institutions in the buckets. (See the equation for UL above.) Therefore, using the OWC methodology rather than the historical averages from Standard and Poor's will result in higher EL but will have an unknown effect on the UL and on overall measures of fund adequacy.

The mapping of credit ratings to PDs makes the implicit assumption that all institutions with the same credit rating have the same probability of failing and that this probability of failing is equal to the historical average default rate. Kealhofer et al. (1998) show that the actual default rate can differ significantly from the historical average default rate. Within a rating grade, the range of default rates is substantial, and the mean default rate can significantly exceed the median default rate (the mean may be almost twice the median). They conclude that the historical average default rate is a noisy estimate of the actual mean. As such, the historical PD is a noisy estimate of the probability of default for any given institution.

If the given institution is a bank, an additional issue arises when historical PDs are used from all industries. Using these mappings of credit ratings to probabilty of default may not be appropriate for the banking sector. If banks have systematically different default risks than other corporate borrowers that are assigned the same credit rating, the mapping may introduce bias in the assignment of probabilities of default. There is reason to believe that this is the case, since banking is a regulated industry. In contrast to most other industries, bank default is a regulatory event: the chartering authority closes a bank. And creditors of a bank are given a different priority to receive payment from the receivership than creditors of a corporation that goes into bankruptcy.

Evidence presented by Nickell, Perraudin, and Varotto (2000) shows that banks have less stable ratings than industrials. BIS (2000) adds further doubt that the PDs from other industrial sectors should be applied to the banking sector. The BIS study suggests that U.S. banks experience a higher default rate than U.S. industrial firms for a given Moody's rating in a given year. Since this suggests that the true relationship between credit ratings and probabilities of default may be different for banks than for other corporate entities, it would be useful to construct a mapping for the banking industry alone.[45]

[45] Of course, this study would also encounter problems. The amount of data available is much smaller for defaults in an individual industry than for defaults in a group of industries. The lack of data may be so severe as to make the study unreliable. Another problem this type of study would face is controlling for legislative changes to bank closing procedures, especially the changes made by FDICIA in 1991.

Appendix C
The KMV Model

The KMV model is based on two theoretical relationships: (1) the value of equity can be viewed as a call option on the value of a firm's assets, and (2) a link exists between the observable volatility of a firm's equity value and the unobservable volatility of asset values. The model has three steps: (1) estimate the asset value and volatility, (2) calculate the distance to default, and (3) map the distance to default into the default probability. The market value of assets and the volatility of assets are generated by an option pricing model. Credit Monitor uses option pricing theory to derive the asset value and its volatility using the market value of equity, the volatility of equity, and the book value of liabilities. Using the market value of assets, Credit Monitor then determines whether the market value of assets is above or below the default point. The default point—the asset value at which the firm will default—usually lies between total liabilities and short-term liabilities and differs from industry to industry. KMV calculates the distance to default (the market net worth, which is the market value of the firm's assets minus the firm's default point divided by the product of the asset value and the asset volatility). The distance to default measures the number of standard deviations the asset value is away from default. KMV then maps the distance to default to the probability of default on the basis of empirical studies of default rates.

Appendix D
Definition of Specialized Lender Categories

The specialized lender categories are defined as follows:[46]

- Agricultural Bank: Agricultural loans and agricultural real-estate loans represent more than 25 percent of total loans.
- Consumer Lender: This category includes both credit-card lenders and other consumer lenders. Consumer lenders are lenders whose residential real estate and consumer loans are more than 50 percent of total assets. Credit-card lenders are lenders whose credit-card loans plus securitized credit-card loans sold are greater than 50 percent of total loans plus securitized credit-card loans sold and whose total loans plus securitized credit-card loans sold are greater than 50 percent of the sum of total assets plus securitized credit-card loans sold.
- Commercial Lender: Commercial and industrial loans, construction loans, multiple family real-estate loans, and nonresidential real-estate loans are greater than 25 percent of total assets.
- Mortgage Lender: Residential real-estate loans and mortgage-backed securities are greater than 50 percent of total assets.
- Multinational Bank: Total assets are greater than $10 billion, and more than 25 percent of total assets are held in foreign offices.
- Other Large: Total assets are greater than $1 billion and the institution is not placed in one of the categories above.

[46] Ross Waldrop of the Division of Insurance and Research, FDIC, created these groupings.

- Other Large Specialized: Total assets are greater than $1 billion, and total loans are less than 40 percent of total assets.
- Other Small Specialized: Total assets are less than or equal to $1 billion, and total loans are less than 40 percent of total assets.
- Other Small: Total assets are less than or equal to $1 billion, and the institution is not placed in one of the categories above.

Table 1

Rating Calibrations

Standard & Poor's Credit Rating	One-Year Default Probability	Moody's Credit Rating	One-Year Default Probability
AAA	0.01%	Aaa	0.01%
AA+	0.02	Aa1	0.02
AA	0.03	Aa2	0.03
AA-	0.04	Aa3	0.04
A+	0.05	A1	0.05
A	0.07	A2	0.07
A-	0.09	A3	0.09
BBB+	0.13	Baa1	0.13
BBB	0.18	Baa2	0.18
BBB-	0.31	Baa3	0.34
BB+	0.53	Ba1	0.63
BB	0.93	Ba2	1.21
BB-	1.57	Ba3	2.25
B+	2.64	B1	4.21
B	4.46	B2	7.86
B-	7.52	B3	12.95

Source: FDIC (2000), 29.
Note: The one-year default probabilities reflect the methodology of Oliver, Wyman & Company.

Table 2

Coverage of Market Data

December 31, 2001

BIF Only

	Total	KMV S&P Ratings	Long-Term Deposit Ratings	KMV PDs
Number	8,342	227	98	772
Total Oakar Adjusted Assets (000 omitted)	$6,866,987,432			
Percent of Total Oakar Adjusted Assets		55.36%	51.44%	62.43%
Total Deposits (000 omitted)	$4,573,065,122			
Percent of Total Deposits		51.12%	47.73%	59.42%
Total Insured Deposits (000 omitted)	$2,689,421,612			
Percent of Total Insured Deposits		41.56%	37.75%	52.01%

BIF and SAIF Merged

	Total	KMV S&P Ratings	Long-Term Deposit Ratings	KMV PDs
Number	9,629	249	105	887
Total Assets (000 omitted)	$7,878,821,894			
Percent of Total Assets		49.85%	40.75%	57.48%
Total Deposits (000 omitted)	$5,194,905,960			
Percent of Total Deposits		42.92%	46.68%	55.17%
Total Insured Deposits (000 omitted)	$2,229,865,881			
Percent of Total Insured Deposits		32.89%	37.05%	47.39%

Table 3

Loss Given Default

Mean, Standard Deviation, and Number of Observations

Asset Size Group	1986–2001	1990–2001	1986–1989	1990–1993	1986–1989 and 1990–1993
Less than $100 Million	24.06%	20.05%	26.29%	20.40%	24.29%
	(13.87)	(12.40)	(14.16)	(12.24)	(13.82)
	n = 977	n = 349	n = 628	n = 322	n = 950
$100 Mil.–$500 Mil.	22.24%	20.05%	26.72%	20.69%	22.90%
	(13.19)	(12.66)	(13.28)	(12.18)	(12.87)
	n = 122	n = 82	n = 40	n = 69	n = 109
$500 Mil.–$1 Bil.	16.40%	17.87%	14.20%	17.87%	16.40%
	(10.53)	(10.08)	(11.75)	(10.08)	(10.53)
	n = 15	n = 9	n = 6	n = 9	n = 15
$1–$5 Billion	15.48%	15.68%	14.80%	12.21%	12.80%
	(15.28)	(16.69)	(10.01)	(8.14)	(8.41)
	n = 23	n = 18	n = 5	n = 17	n = 22
Larger than $5 Billion	8.72%	4.38%	14.14%	4.38%	8.72%
	(6.94)	(4.88)	(5.10)	(4.88)	(6.94)
	n = 9	n = 5	n = 4	n = 5	n = 9
All Size Groups	23.47%	19.67%	26.05%	19.87%	23.69%
	(13.88)	(12.63)	(14.11)	(12.19)	(13.74)
	n = 1,146	n = 463	n = 683	n = 422	n = 1,105

Source: FDIC, *Failed Bank Cost Analysis*, 1986–2001, and consolidation of receiverships as performed by the FDIC Division of Finance.

Note: Loss given default is defined as the loss to the FDIC as a percentage of total assets at failure.

Table 4

Results from Baseline Simulations

BIF Only	
	Baseline
Expected Loss (EL) (000 omitted)	$1,169,392
Unexpected Loss (UL)	$4,022,597
A Rating (99.93%) Reserve Ratio	2.84
A- Rating (99.91%) Reserve Ratio	2.46
BBB+ Rating (99.87%) Reserve Ratio	1.91
BBB Rating (99.82%) Reserve Ratio	1.61
Reserve Ratio (Percent)	1.26
BIF Balance (000 omitted)	$30,439,000
Insured Deposits (000 omitted)	$2,408,350,000

BIF and SAIF Merged	
	Baseline
Expected Loss (EL) (000 omitted)	$1,640,655
Unexpected Loss (UL) (000 omitted)	$5,295,691
A Rating (99.93%) Reserve Ratio	2.54
A- Rating (99.91%) Reserve Ratio	2.33
BBB+ Rating (99.87%) Reserve Ratio	1.95
BBB Rating (99.82%) Reserve Ratio	1.61
Reserve Ratio, 12/31/2001	1.29
BIF and SAIF Balance	$41,374,000
Insured Deposits	$3,210,708,000

Table 5
Comparison of Probabilities of Default

BIF Only

	Baseline	Historical PDs	Logit PDs Only	S&P and Logit PDs
Expected Loss (EL)	$1,169,392	$1,707,983	$376,018	$413,662
Unexpected Loss (UL)	$4,022,597	$5,836,769	$2,697,391	$2,521,570
A Rating (99.93%) Reserve Ratio	2.84	3.76	1.93	1.75
A- Rating (99.91%) Reserve Ratio	2.46	3.58	1.74	1.48
BBB+ Rating (99.87%) Reserve Ratio	1.91	3.12	1.32	1.09
BBB Rating (99.82%) Reserve Ratio	1.61	2.69	1.04	0.92
Reserve Ratio, 12/31/2001	1.26	1.26	1.26	1.26
BIF Balance	$30,439,000	$30,439,000	$30,439,000	$30,439,000
Insured Deposits	$2,408,350,000	$2,408,350,000	$2,408,350,000	$2,408,350,000
Mean of PD	0.236%	0.2400%	0.0626%	0.0642%
Standard Deviation of PD	0.026%	n.a.	0.8625%	0.8625%

BIF and SAIF Merged

	Baseline	Historical PDs	Logit PDs Only	S&P and Logit PDs
Expected Loss (EL)	$1,640,655	$2,161,440	$544,295	$647,894
Unexpected Loss (UL)	$5,295,691	$7,352,416	$3,439,357	$3,123,785
A Rating (99.93%) Reserve Ratio	2.54	3.37	1.80	1.41
A- Rating (99.91%) Reserve Ratio	2.33	3.15	1.44	1.28
BBB+ Rating (99.87%) Reserve Ratio	1.95	2.75	1.22	1.07
BBB Rating (99.82%) Reserve Ratio	1.61	2.36	1.03	0.94
Reserve Ratio	1.29	1.29	1.29	1.29
BIF and SAIF Balance	$41,374,000	$41,374,000	$41,374,000	$41,374,000
Insured Deposits	$3,210,708,000	$3,210,708,000	$3,210,708,000	$3,210,708,000
Mean of EDF	0.237%	0.2400%	0.0666%	0.0693%
Standard Deviation of EDF	0.035%	n.a.	0.8202%	0.8242%

Table 6
Logistic Regression of the Incidence of Failure One Year Following Condition Measurement
(1984–2000 year-end Call Data)

Explanatory Variable	Coefficient Estimate (Standard Error)
Intercept	-6.9443 (0.2335)*
Equity plus loss reserves	-0.4125 (0.0154)*
Loans past due 30–89 days	0.1456 (0.0144)*
Loans past due 90 days or more	0.1455 (0.0070)*
Gross loan charge-offs	0.0182 (0.0042)*
Net income	-0.0060 (0.0012)*
Capital rating	0.1454 (0.0662)
Asset rating	0.2101 (0.0629)*
Management rating	0.3325 (0.0537)*
Earnings rating	0.1307 (0.0560)
Liquidity rating	0.4851 (0.0449)*
"Age" of examination data	0.6520 (0.0351)*
Pseudo R Squared = 56.48%	
Somers' D = 0.948	

* Significant at the 1% confidence level.

Table 7

Comparison of Market Information

BIF Only

	Baseline	PDs from Deposit Ratings	PDs from KMV
Expected Loss (EL)	$1,169,392	$1,125,946	$2,504,834
Unexpected Loss (UL)	$4,022,597	$3,791,366	$7,696,773
A Rating (99.93%) Reserve Ratio	2.84	2.60	4.41
A- Rating (99.91%) Reserve Ratio	2.46	2.26	4.19
BBB+ Rating (99.87%) Reserve Ratio	1.91	1.72	3.81
BBB Rating (99.82%) Reserve Ratio	1.61	1.40	3.46
Reserve Ratio	1.26	1.26	1.26
BIF Balance 12/31/2001	$30,439,000	$30,439,000	$30,439,000
Insured Deposits	$2,408,350,000	$2,408,350,000	$2,408,350,000
Mean of PD	0.236%	0.238%	0.267%
Standard Deviation of PD	0.026%	0.021%	0.348%

BIF and SAIF Merged

	Baseline	PDs from Deposit Ratings	PDs from KMV
Expected Loss (EL)	$1,640,655	$1,553,657	$3,166,980
Unexpected Loss (UL)	$5,295,691	$5,180,078	$8,978,069
A Rating (99.93%) Reserve Ratio	2.54	2.54	3.72
A- Rating (99.91%) Reserve Ratio	2.33	2.31	3.46
BBB+ Rating (99.87%) Reserve Ratio	1.95	1.95	3.11
BBB Rating (99.82%) Reserve Ratio	1.61	1.60	2.84
Reserve Ratio	1.29	1.29	1.29
BIF and SAIF Balance 12/31/2001	$41,374,000	$41,374,000	$41,374,000
Insured Deposits	$3,210,708,000	$3,210,708,000	$3,210,708,000
Mean of PD	0.237%	0.239%	0.270%
Standard Deviation of PD	0.082%	0.022%	0.402%

Table 8

Comparison of Loss Given Default

BIF Only

	Baseline	1990–2001 Loss Rates	1986–1989 Loss Rates	1990–1993 Loss Rates	1986–1989 and 1990–1993 Loss Rates
Expected Loss (EL)	$1,169,392	$900,431	$1,515,637	$872,020	$1,149,636
Unexpected Loss (UL)	$4,022,597	$2,610,866	$5,484,400	$2,560,620	$3,994,062
A Rating (99.93%) Reserve Ratio	2.84	1.64	4.08	1.64	2.84
A- Rating (99.91%) Reserve Ratio	2.46	1.41	3.69	1.39	2.47
BBB+ Rating (99.87%) Reserve Ratio	1.91	1.07	3.20	1.07	1.92
BBB Rating (99.82%) Reserve Ratio	1.61	0.92	2.74	0.89	1.60
Reserve Ratio	1.26	1.26	1.26	1.26	1.26
BIF Balance 12/31/2001	$30,439,000	$30,439,000	$30,439,000	$30,439,000	$30,439,000
Insured Deposits	$2,408,350,000	$2,408,350,000	$2,408,350,000	$2,408,350,000	$2,408,350,000
Mean of LGD	22.51%	19.53%	25.30%	19.83%	22.78%
Standard Deviation of LGD	2.82%	2.19%	3.56%	2.59%	3.14%

BIF and SAIF Merged

	Baseline	1990–2001 Loss Rates	1986–1989 Loss Rates	1990–1993 Loss Rates	1986–1989 and 1990–1993 Loss Rates
Expected Loss (EL)	$1,640,655	$1,262,349	$2,112,659	$1,205,290	$1,599,278
Unexpected Loss (UL)	$5,295,691	$3,531,311	$6,967,471	$3,438,925	$5,240,100
A Rating (99.93%) Reserve Ratio	2.54	1.54	3.47	1.54	2.54
A- Rating (99.91%) Reserve Ratio	2.33	1.39	3.21	1.38	2.33
BBB+ Rating (99.87%) Reserve Ratio	1.95	1.19	2.77	1.16	1.95
BBB Rating (99.82%) Reserve Ratio	1.61	0.99	2.45	0.98	1.59
Reserve Ratio	1.29	1.29	1.29	1.29	1.29
BIF and SAIF Balance 12/31/2001	$41,374,000	$41,374,000	$41,374,000	$41,374,000	$41,374,000
Insured Deposits	$3,210,708,000	$3,210,708,000	$3,210,708,000	$3,210,708,000	$3,210,708,000
Mean of LGD	22.41%	19.49%	25.19%	19.78%	22.67%
Standard Deviation of LGD	2.91%	2.26%	3.71%	2.69%	3.26%

Table 9

Comparison of Bucketing Techniques

BIF Only

	Baseline	25 Equal-Sized Buckets	Size and Region Buckets	Region and CAMELS Group
Expected Loss (EL)	$1,169,392	$1,189,312	$1,164,688	$1,188,561
Unexpected Loss (UL)	$4,022,597	$3,871,454	$3,293,780	$4,233,094
A Rating (99.93%) Reserve Ratio	2.84	2.75	2.54	3.05
A- Rating (99.91%) Reserve Ratio	2.46	2.49	2.33	2.72
BBB+ Rating (99.87%) Reserve Ratio	1.91	2.11	1.89	2.28
BBB Rating (99.82%) Reserve Ratio	1.61	1.73	1.59	1.88
Reserve Ratio	1.26	1.26	1.26	1.26
BIF Balance 12/31/2001	$30,439,000	$30,439,000	$30,439,000	$30,439,000
Insured Deposits	$2,408,350,000	$2,408,350,000	$2,408,350,000	$2,408,350,000

BIF and SAIF Merged

	Baseline	25 Equal-Sized Buckets	Size and Region Buckets	Region and CAMELS Group	Size and CAMELS Group
Expected Loss (EL)	$1,640,655	$1,524,121	$1,639,434	$1,658,511	$1,638,497
Unexpected Loss (UL)	$5,295,691	$4,791,091	$5,296,570	$5,091,764	$5,154,308
A Rating (99.93%) Reserve Ratio	2.54	2.20	2.56	2.43	2.32
A- Rating (99.91%) Reserve Ratio	2.33	1.99	2.32	2.10	2.10
BBB+ Rating (99.87%) Reserve Ratio	1.95	1.70	1.96	1.90	1.85
BBB Rating (99.82%) Reserve Ratio	1.61	1.45	1.63	1.62	1.61
Reserve Ratio	1.29	1.29	1.29	1.29	1.29
BIF and SAIF Balance 12/31/2001	$41,374,000	$41,374,000	$41,374,000	$41,374,000	$41,374,000
Insured Deposits	$3,210,708,000	$3,210,708,000	$3,210,708,000	$3,210,708,000	$3,210,708,000

Table 9 (continued)

Comparison of Bucketing Techniques

	BIF Only	
	Baseline	**Specialized Lender and Region**
Expected Loss (EL)	$1,169,392	$1,196,005
Unexpected Loss (UL)	$4,022,597	$4,361,731
A Rating (99.93%) Reserve Ratio	2.84	3.05
A- Rating (99.91%) Reserve Ratio	2.46	2.72
BBB+ Rating (99.87%) Reserve Ratio	1.91	2.28
BBB Rating (99.82%) Reserve Ratio	1.61	1.88
Reserve Ratio	1.26	1.26
BIF Balance 12/31/2001	$30,439,000	$30,439,000
Insured Deposits	$2,408,350,000	$2,408,350,000

	BIF and SAIF Merged	
	Baseline	**Specialized Lender and Region**
Expected Loss (EL)	$1,640,655	$1,647,041
Unexpected Loss (UL)	$5,295,691	$5,322,268
A Rating (99.93%) Solvency	2.54	2.58
A- Rating (99.91%) Solvency	2.33	2.41
BBB+ Rating (99.87%) Solvency	1.95	2.03
BBB Rating (99.82%) Solvency	1.61	1.66
Reserve Ratio	1.29	1.29
BIF and SAIF Balance 12/31/2001	$41,374,000	$41,374,000
Insured Deposits	$3,210,708,000	$3,210,708,000

Table 10

Size and Region Buckets

December 31, 2001

BIF Institutions

	Northeast	Southeast	Central and Midwest	Southwest	West	Total
Less than $100 Million	216	628	2,456	824	411	**4,535**
$100–$500 Million	482	613	1,128	445	338	**3,006**
$500 Mil.–$1 Billion	101	64	113	38	54	**370**
$1–$5 Billion	98	37	68	27	58	**288**
More than $5 Billion	52	24	38	8	21	**143**
Total	**949**	**1,336**	**3,803**	**1,342**	**882**	**8,342**

BIF and SAIF Institutions

	Northeast	Southeast	Central and Midwest	Southwest	West	Total
Less than $100 Million	340	724	2,699	873	432	**5,068**
$100–$500 Million	624	706	1,349	485	380	**3,544**
$500 Mil.–$1 Billion	132	87	139	44	67	**469**
$1–$5 Billion	120	48	91	37	77	**373**
More than $5 Billion	59	28	48	10	30	**175**
Total	**1,275**	**1,593**	**4,326**	**1,449**	**986**	**9,629**

Note: The Northeast region includes the following states: Connecticut, Delaware, District of Columbia, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. The Southeast region includes the following states: Alabama, Florida, Georgia, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia. The Central and Midwest region includes the following states: Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. The Southwest region includes the following states: Arkansas, Louisiana, New Mexico, Oklahoma, and Texas. The West includes the following states: Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, Oregon, Utah, Washington, and Wyoming.

Table 11

CAMELS Ratings

December 31, 2001

BIF Institutions	
Composite CAMELS Rating	**Total**
1	**3,174**
2	**4,520**
3	**444**
4	**107**
5	**19**
Total	**8,264**

BIF and SAIF Institutions	
Composite CAMELS Rating	**Total**
1	**3,609**
2	**5,247**
3	**528**
4	**131**
5	**22**
Total	**9,537**

Note: There were 92 institutions that did not have CAMELS ratings.

Table 12

Industry Specialization and Region Buckets

December 31, 2001

BIF Institutions

	Northeast	Southeast	Central and Midwest	Southwest	West	Total
Agricultural Bank	2	47	1,437	274	102	1,862
Consumer Lender	42	38	106	16	33	235
Commercial Lender	401	862	1,306	508	596	3,673
Mortgage Lender	232	34	92	31	48	437
Multinational Bank	5	n.a.	n.a.	n.a.	n.a.	5
Other Large Specialized Lenders	12	1	3	4	3	23
Other Large Lenders	27	13	16	8	4	68
Other Small Specialized Lenders	63	83	99	146	56	447
Other Small Institutions	165	288	744	355	40	1,592

BIF and SAIF Institutions

	Northeast	Southeast	Central and Midwest	Southwest	West	Total
Agricultural Bank	3	47	1,442	277	102	1,871
Consumer Lender	46	47	131	23	38	285
Commercial Lender	437	948	1,408	537	649	3,979
Mortgage Lender	475	145	448	86	88	1,242
Multinational Bank	5	n.a.	n.a.	n.a.	n.a.	5
Other Large Specialized Lenders	13	1	4	4	3	25
Other Large Lenders	31	14	17	10	5	77
Other Small Specialized Lenders	80	87	105	147	60	479
Other Small Institutions	185	304	771	365	41	1,666

Table B.1

Comparison of Rating Calibrations with Standard and Poor's Historical Default Rates

Standard and Poor's Rating	Historical One-Year Default Rates, 1981–1999	Oliver, Wyman & Company One-Year Default Probability
AAA	0.00%	0.01%
AA+	0.00	0.02
AA	0.00	0.03
AA-	0.03	0.04
A+	0.02	0.05
A	0.05	0.07
A-	0.03	0.09
BBB+	0.13	0.13
BBB	0.22	0.18
BBB-	0.29	0.31
BB+	0.57	0.53
BB	0.89	0.93
BB-	1.14	1.57
B+	2.66	2.64
B	8.46	4.46
B-	10.19	7.52

Sources: Historical one-year default rates, 1981–1999, are from Brand and Bahar (2000), 15; Oliver, Wyman & Company one-year default probabilities from FDIC (2000), 29.

Table B.2

Comparison of Rating Calibrations with Moody's Historical Default Rates

Moody's Rating	Historical One-Year Default Rates, 1983–1999	Oliver, Wyman & Company One-Year Default Probability
Aaa	0.00%	0.01%
Aa1	0.00	0.02
Aa2	0.00	0.03
Aa3	0.07	0.04
A1	0.00	0.05
A2	0.00	0.07
A3	0.00	0.09
Baa1	0.04	0.13
Baa2	0.07	0.18
Baa3	0.31	0.34
Ba1	0.62	0.63
Ba2	0.53	1.21
Ba3	2.52	2.25
B1	3.46	4.21
B2	6.88	7.86
B3	12.23	12.95

Sources: Historical one-year default rates, 1983-1999, are from Keenan et al. (2000), 27; Oliver, Wyman & Company one-year default probabilities from FDIC (2000), 29.

Figure 1
Credit Loss Distribution

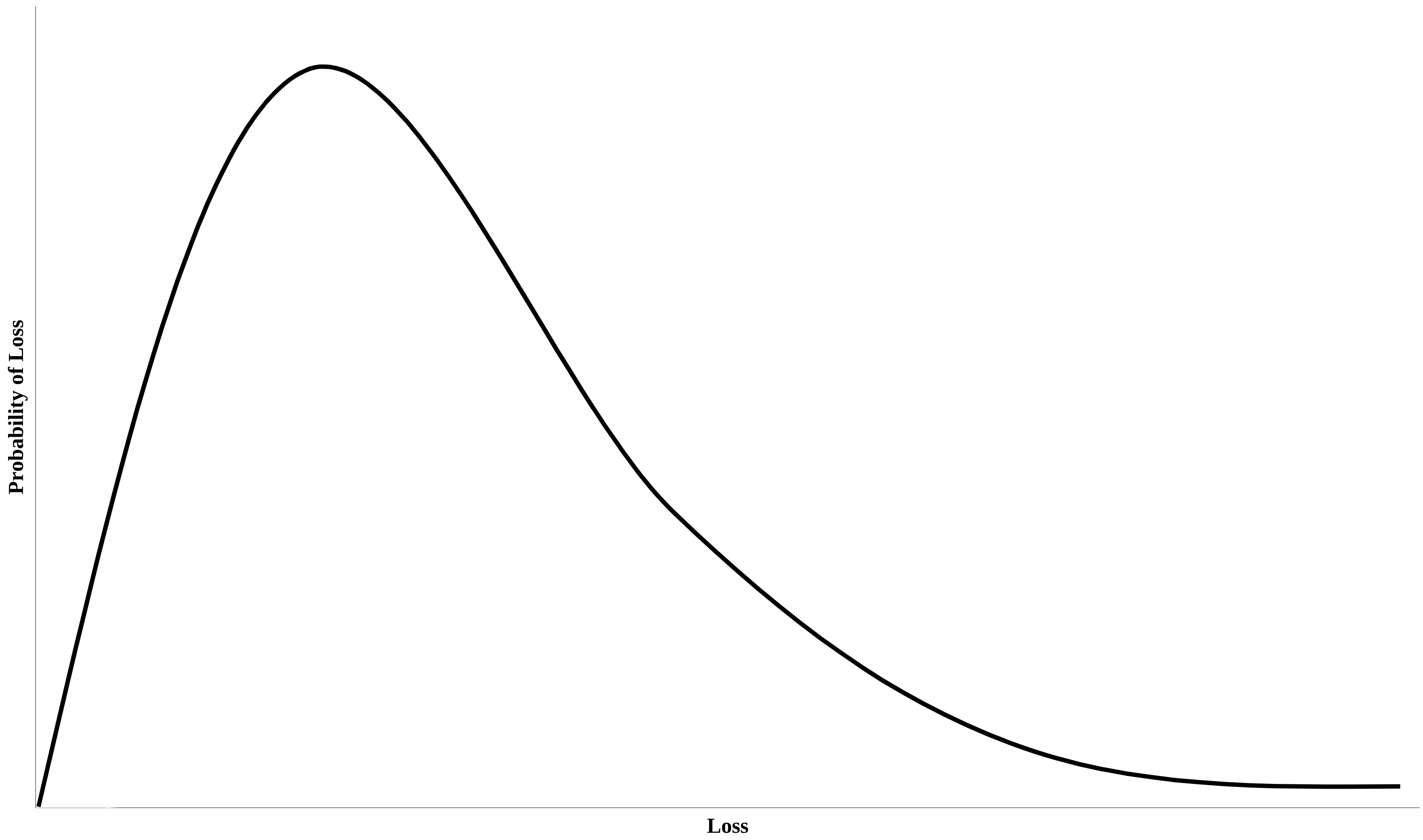

Figure 2
Baseline Simulation
BIF

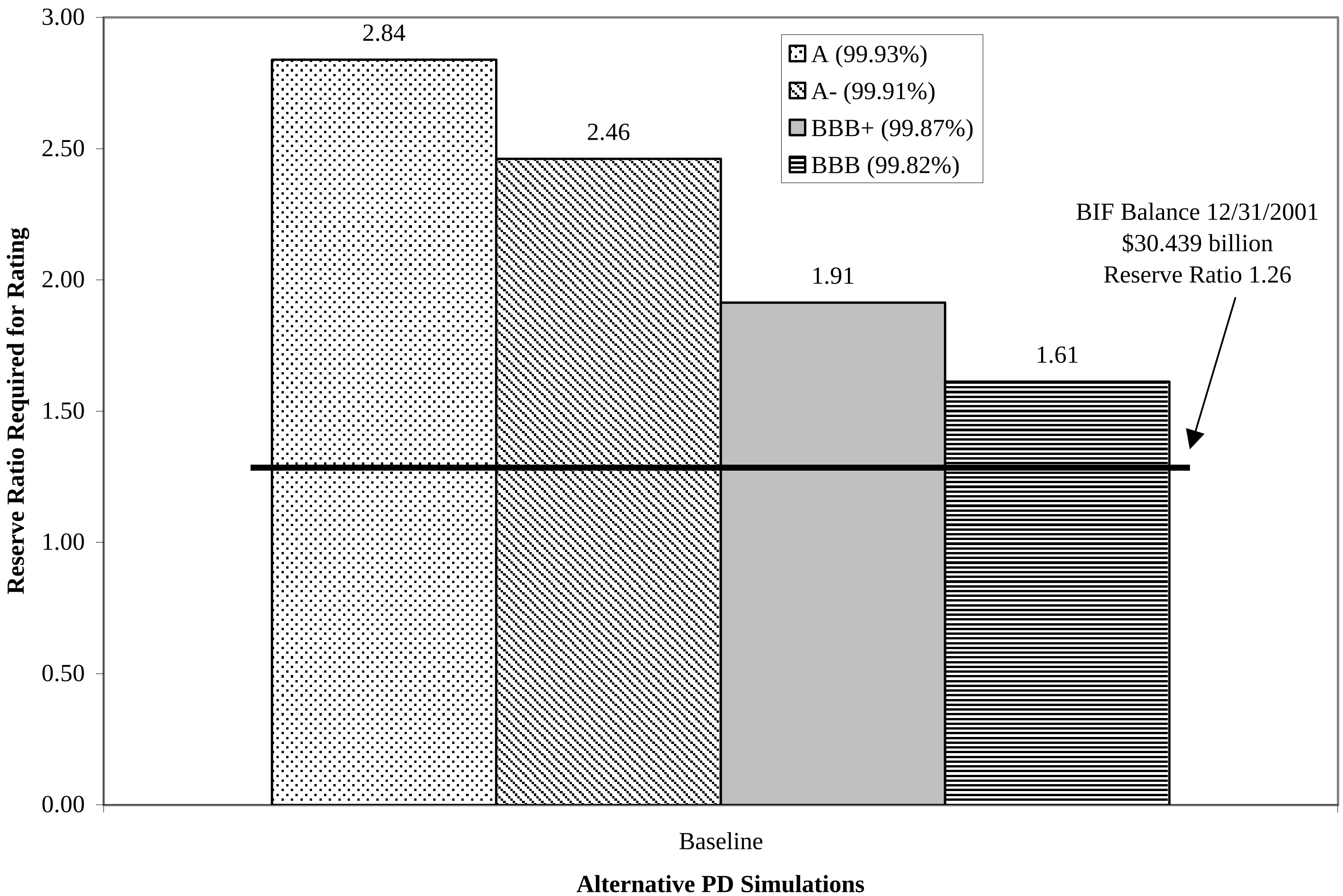

Figure 3
Baseline Simulation
BIF and SAIF Merged

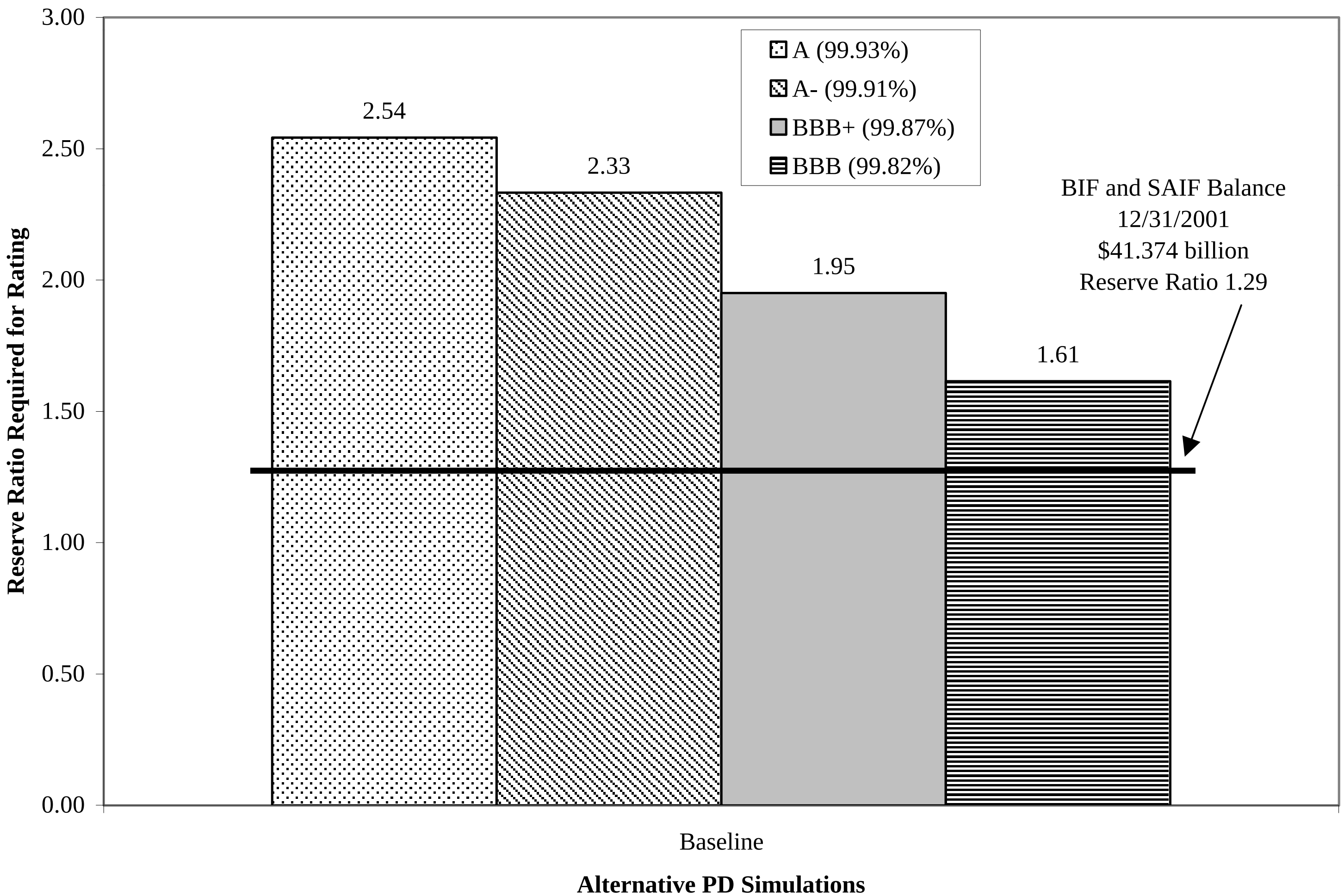

Figure 4
Sensitivity Analysis: Probabilities of Default
BIF

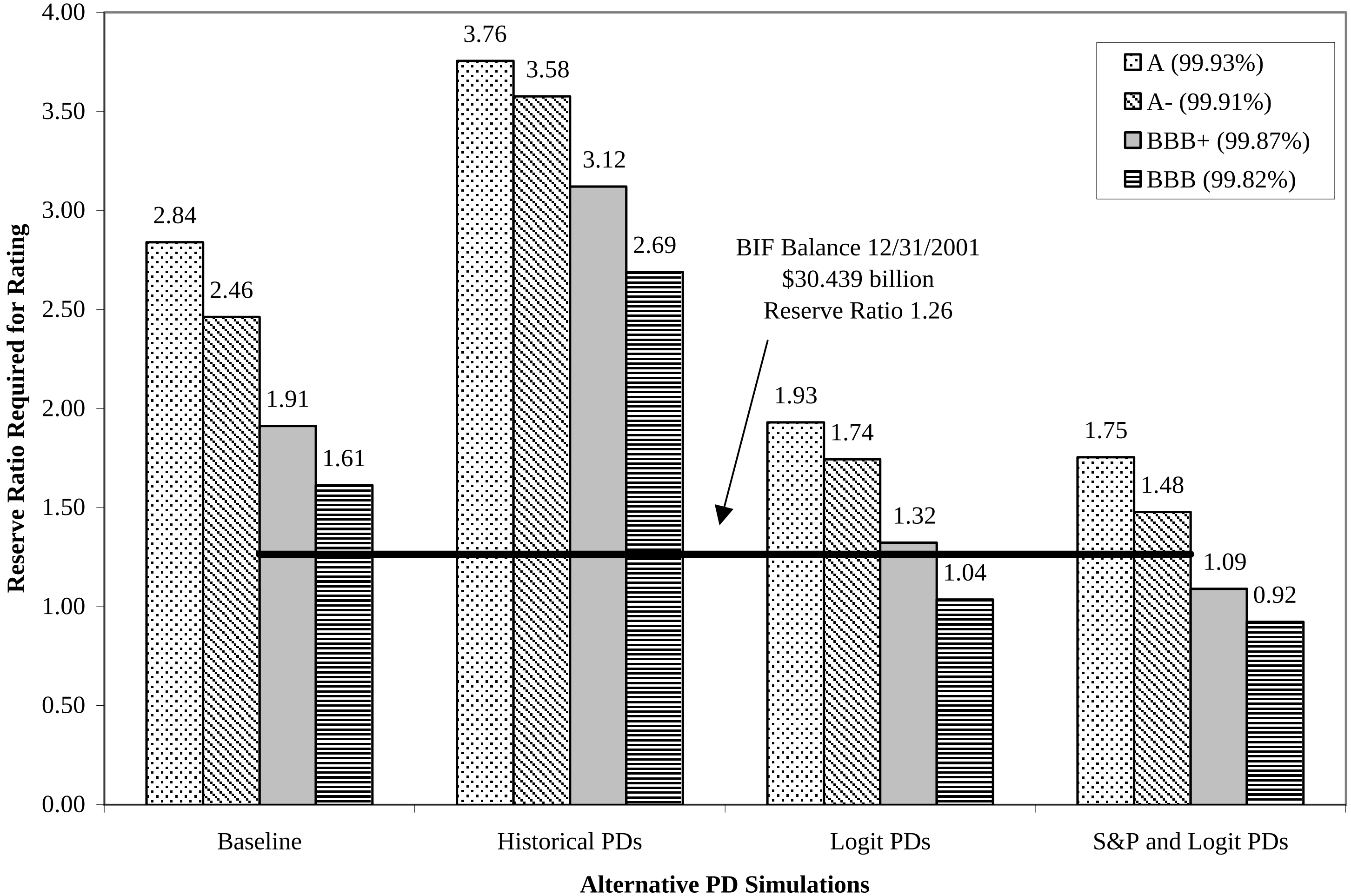

Figure 5
Sensitivity Analysis: Probabilities of Default
BIF and SAIF Merged

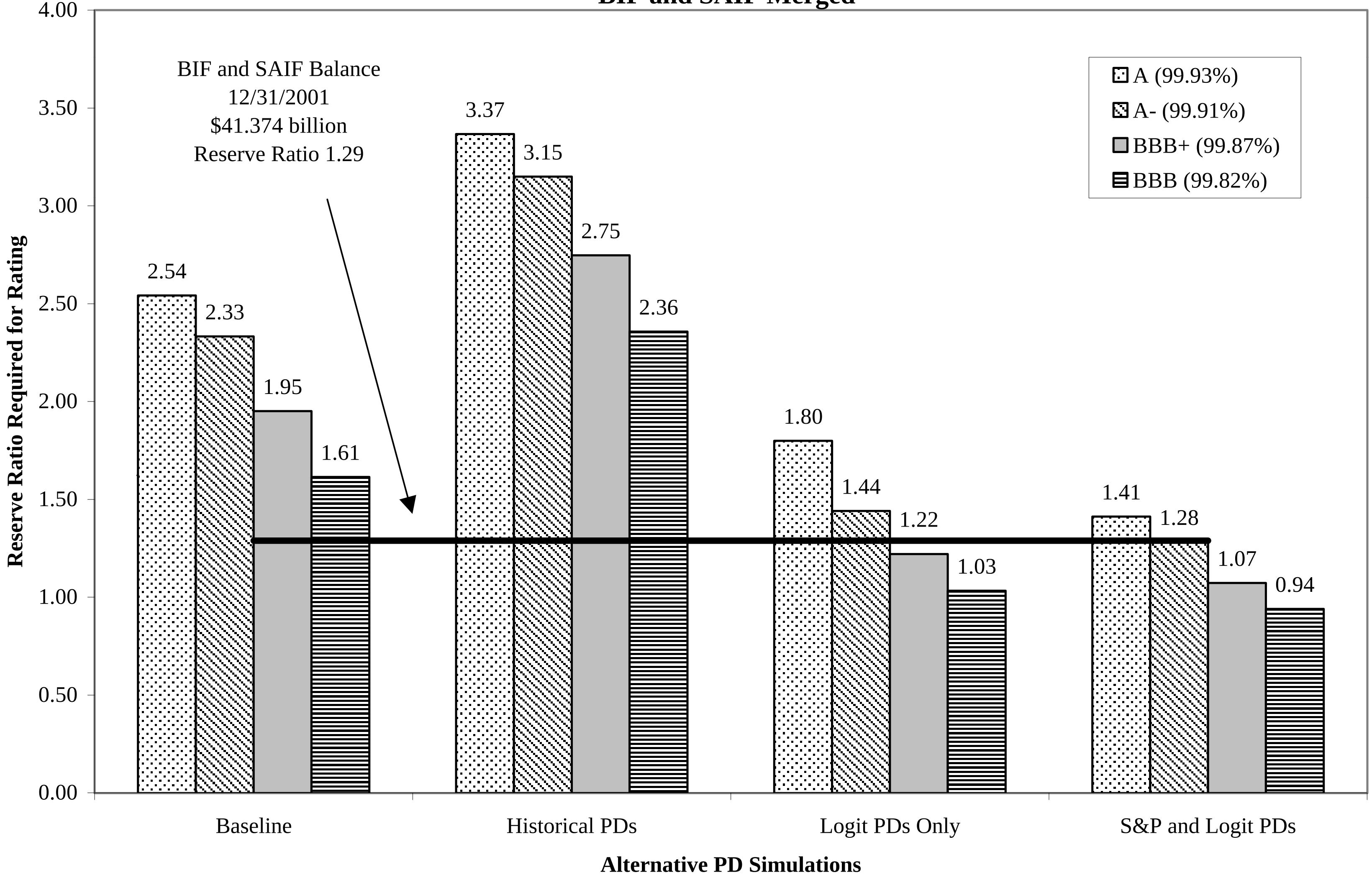

Figure 6
Sensitivity Analysis: PDs from Market Information
BIF

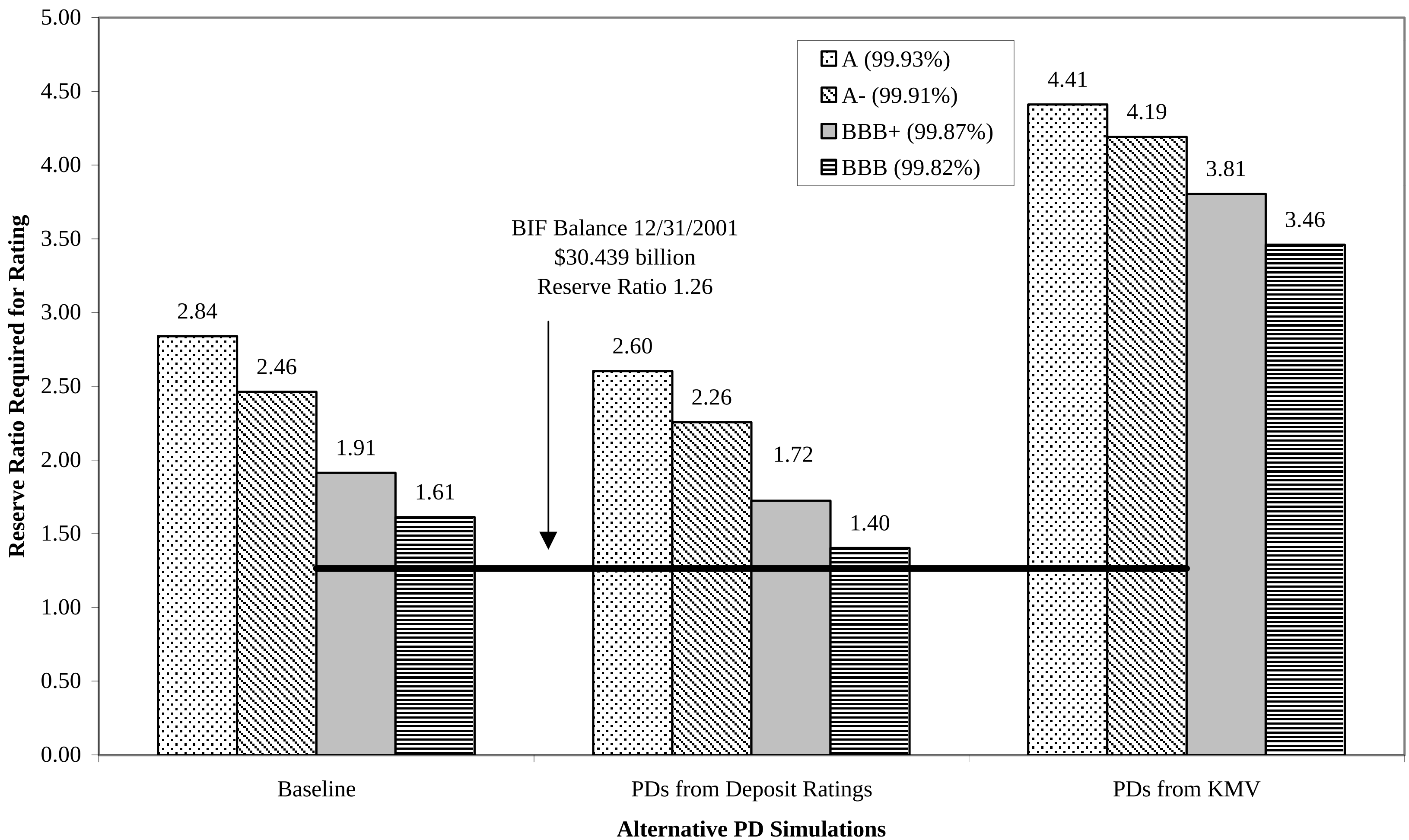

Figure 7
Sensitivity Analysis: PDs from Market Information
BIF and SAIF Merged

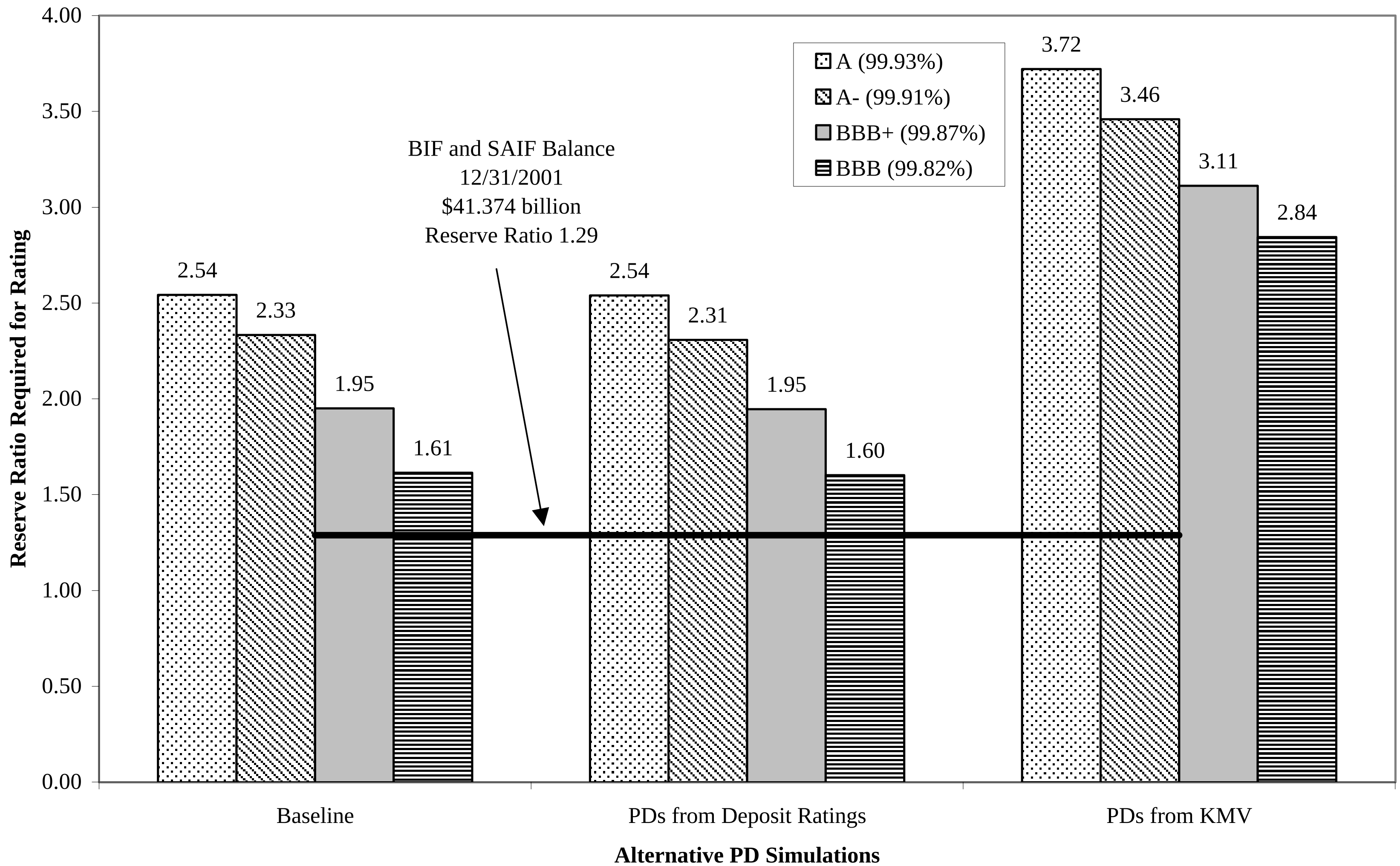

Figure 8
Sensitivity Analysis: Loss Given Default
BIF

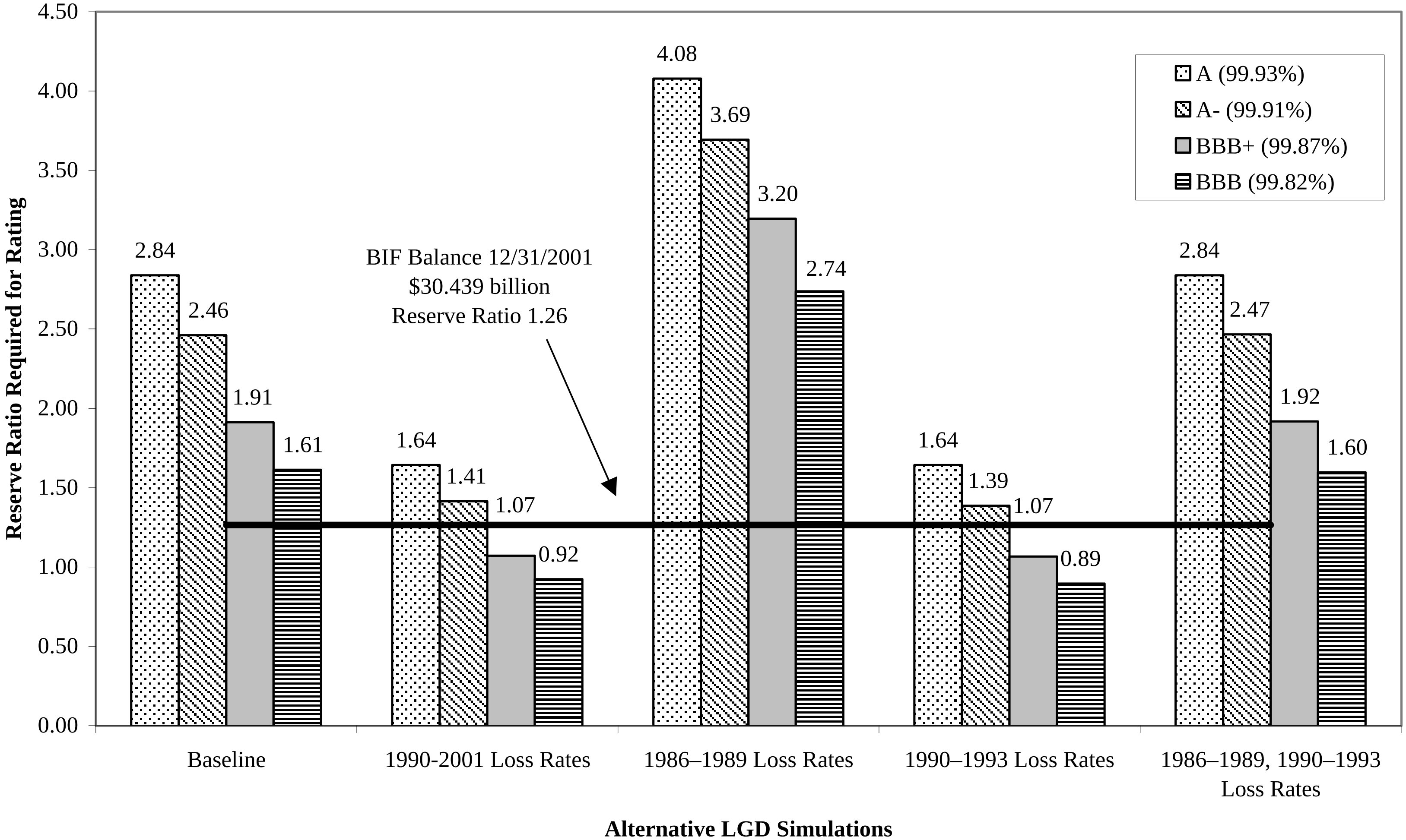

Figure 9
Sensitivity Analysis: Loss Given Default
BIF and SAIF Merged

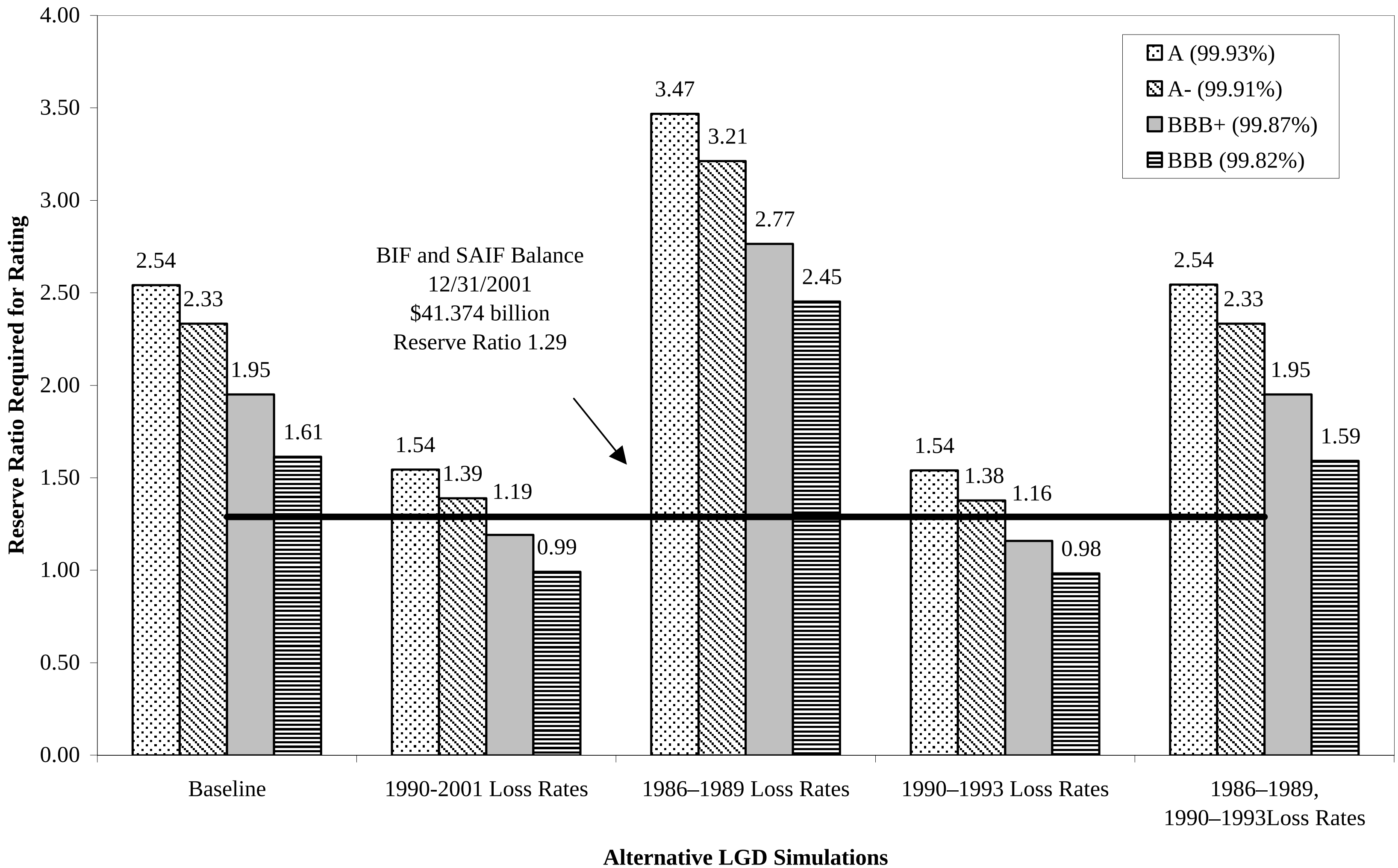

Figure 10
Sensitivity Analysis: Bucketing
BIF

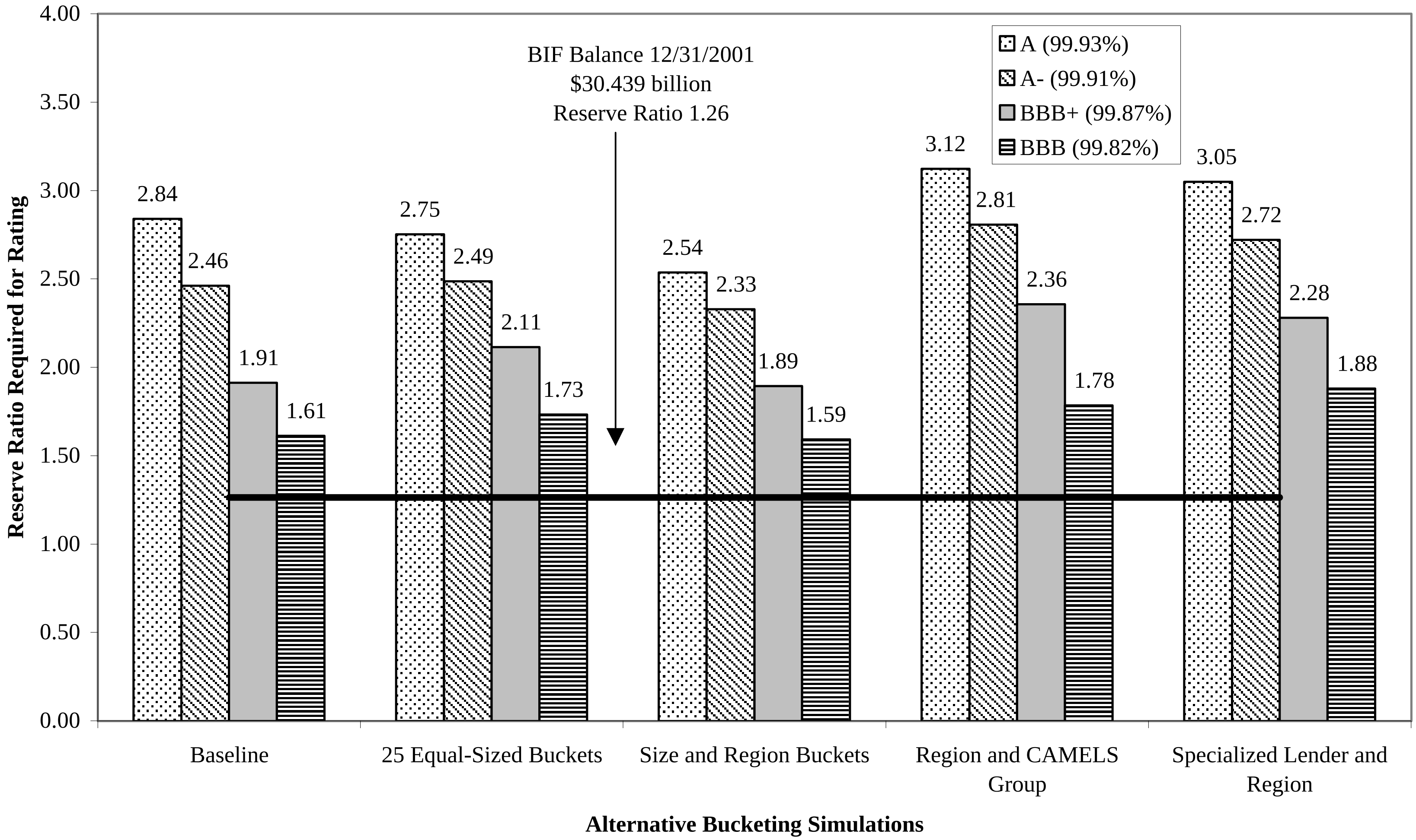

Figure 11
Sensitivity Analysis: Bucketing
BIF and SAIF Merged